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CONVERGENCE ACCELERATION AND ERROR ANALYSIS OF  
THE DISCRETE ORDINATES ALGORITHM  
IN PLANE GEOMETRY

by

Gerald Lloyd Atkinson

A dissertation submitted in partial fulfillment  
of the requirements for the degree of  
Doctor of Philosophy  
(Nuclear Engineering)  
in The University of Michigan  
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T143 625



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## NOMENCLATURE

$\psi(x, \mu)$	Angular flux solution of analytic transport equation in plane geometry
$\psi_j(x)$	Solution of $S_N$ equations
$\underline{\psi}^*$	Exact vector solution of spatially discretized $S_N$ algorithm
$\psi_{k,j}^{(i)}$	Component of $i^{th}$ iterate approximation to $\underline{\psi}^*$
$\underline{\psi}^{(i)}$	Vector representation of solution set $\{\psi_{k,j}^{(i)}\}$
$\psi_k^{(i)}$	$k^{th}$ component of vector $\underline{\psi}^{(i)}$
$L$	Matrix operator for fully discretized system
D-E	Matrix containing the effects of streaming and collision
$S$	Scattering matrix
$   \quad   $	Norm of the matrix or vector within
$q(x, \mu)$	Inhomogeneous source term
$x$	Spatial variable
$\mu$	Direction cosine of angle between particle motion and the X-axis
$w_j$	$j^{th}$ weight in the quadrature set $\{w_j, \mu_j\}$
$\sigma_t$	Macroscopic total cross section
$\sigma_s$	Macroscopic scattering cross section
$\Delta$	Spatial increment of the mesh
$R$	Number of spatial increments in the slab width
$N$	Number of angular ordinates in the set $\{\mu_j\}$
$\underline{e}^{(i)}$	Iteration error in the $i^{th}$ iterate approximation
$d_j$	Coefficient in the unmodified $S_N$ algorithm



$e_j$	Coefficient in the unmodified $S_N$ algorithm
$\underline{\delta}^{(i)}$	Difference between successive iterate solutions
$\alpha$	Acceleration parameter, positive real constant
$\epsilon$	Arbitrarily small positive real constant
$\beta$	Positive real constant
$\gamma$	Positive real constant
$\phi_j(x)$	Transform domain solution of angular discretized $S_N$ equations
$\underline{\phi}^*$	Exact vector solution of spatially discretized transform domain $S_N$ algorithm
$\phi_{k,j}^{(i)}$	Component of $i^{th}$ iterate approximation to $\underline{\phi}^*$
$\underline{\phi}^{(i)}$	Vector representation of solution set $\{\phi_{k,j}^{(i)}\}$
$\phi_k^{(i)}$	$k^{th}$ component of vector $\underline{\phi}^{(i)}$
$e_j$	Coefficient in transform domain algorithm
$d_j$	Coefficient in transform domain algorithm
D-E	Transform domain matrix with same form as D-E but with matrix elements containing the acceleration parameter $\alpha$
$\tau_j(x)$	Discretization error
$\rho$	Condition number of iteration matrix (in Chapter V)
$\nu$	Condition number of matrix D-E
$\delta E$	Uncertainty in the matrix E
$\delta D$	Uncertainty in the matrix D
$\underline{\delta q}$	Uncertainty in the vector $\underline{q}$
$\underline{\delta \psi}^{(i)}$	Uncertainty in the iterate solution $\underline{\psi}^{(i)}$



## CHAPTER I

### INTRODUCTION TO DISCRETE ORDINATES METHODS IN TRANSPORT THEORY

#### Transport Theory

The behavior of a nuclear reactor and the effectiveness of its shield are governed by the distribution in space, velocity, and time of the neutrons and photons in the system. The transport equation is a statement of conservation for these neutral particles, the solution of which determines their distribution in phase space. Derivation of the transport equation is presented in most transport theory texts.<sup>1-3</sup>

A few special systems have exact solutions,<sup>4,5</sup> but for more practical systems, numerical solutions of an approximate transport equation are sought. A few of the more useful transport approximations are spherical harmonics<sup>6</sup> Monte Carlo,<sup>7</sup> discrete ordinates,<sup>8</sup> and moments methods.<sup>9</sup>

The spherical harmonics method treats the anisotropy of the particle distribution and cross sections to various degrees of approximation. Its application to plane, spherical, and cylindrical geometries has been useful but for more complex geometries, the spherical harmonics method is so complicated that other methods are used.



The moments method, used in shielding studies, calculates particle transport rigorously but the method is limited to infinite homogeneous media.

The discrete ordinates and Monte Carlo methods are the most nearly rigorous for multidimensional problems but the former is hampered by ray-effects<sup>10</sup> and is currently limited to two-dimensional problems. The Monte Carlo method is the only useful technique for rigorous solution of three-dimensional problems.

#### Development of Discrete Ordinate Method

The use of discrete ordinates was first suggested by Wick in 1943<sup>11</sup> and developed for radiation transport in stellar atmospheres by Chandrasekhar.<sup>12,13</sup> Carlson introduced the angular "segmented"  $S_N$  approximation for radiation transport calculations at Los Alamos in late 1952 and early 1953.<sup>14</sup> A complete history of  $S_N$  development is given by Carlson<sup>15</sup> and a current bibliography is available.<sup>16</sup> Chernick<sup>17</sup> gives a detailed historical review of reactor physics calculation methods from the Manhattan Project of the 1940's to the present and describes the place of  $S_N$  computer codes in reactor criticality and shielding applications.

Early  $S_N$  methods have been refined to the present "diamond difference" scheme, described by Carlson,<sup>8</sup> which is incorporated in most  $S_N$  codes. New approximations, such as  $MS_N$ ,<sup>18</sup> have been derived for special problems.





In 1967 Shreiner<sup>19</sup> attempted to derive an  $S_N$  difference scheme, called  $VS_N$ , from a variational principle but produced no improvement over existing methods. More recently, effort has been expended to derive discrete ordinate approximations from space-angle synthesis techniques.<sup>20</sup> Kaplan<sup>21</sup> derives an  $S_2$  approximation in  $X, Y$  geometry in this manner by using step functions in direction as trial functions to eliminate ray effects. Natelson<sup>22</sup> derives discrete ordinate approximations from a first-order variational principle in  $X, Y$  geometry. For some unknown reason, this approach has not led to improved difference schemes over the standard diamond difference  $S_N$  method.

#### Applications of $S_N$ Method

Transport theory, as opposed to one of the simpler approximation techniques such as diffusion theory, must be used when either very precise solutions are required or flux variations are large. As a rule of thumb, transport theory is used when the logarithmic gradient of the particle flow density is of the order of or larger than an inverse mean free path over significant portions of the system. Early application of  $S_N$  by Lee<sup>23</sup> to the one-speed problem revealed that the  $S_8$  approximation gave critical radii within 0.3% of the values obtained by the exact solution of the neutron transport equation. Problems exist, however, for which the one-speed approximation is not sufficient. Mills<sup>24</sup> applying  $S_N$  to small fast critical assemblies such as Godiva, Jezebel, and Topsy, revealed that 24-group,  $S_8$



calculations with a  $P_2$  approximation to the scattering anisotropy should be sufficient to provide an accurate treatment of neutron transport in fast metal assemblies.

More recently, the demand for tighter safety standards has awakened renewed interest in application of transport theory  $S_N$  approximations. Protsik<sup>25</sup> compared results of multigroup diffusion theory and  $S_N$  calculations and found that significant error in loss-of-coolant reactivity calculations occurs using diffusion theory. He found that diffusion theory over-predicts the neutron leakage and under-predicts the multiplication.

The  $S_N$  approximation has also been used as a standard, for problems without an exact solution, by which the merits of other techniques are judged.<sup>26-28</sup>  $S_N$  solutions of the adjoint equation have been used in importance sampling techniques for Monte Carlo methods.<sup>29</sup>

### Multigroup $S_N$ Equations

The steady-state multigroup transport equations can be written<sup>30</sup>

$$L\psi(\underline{r}, \hat{\Omega}) = S\psi(\underline{r}, \hat{\Omega}) + q(\underline{r}, \hat{\Omega}) \quad (1)$$

where the vectors  $\psi$  and  $q$  contain the unknown distributions and sources in each energy group, respectively. The operators  $L$  and  $S$  take the following forms

$$(L\psi(\underline{r}, \hat{\Omega}))_g = \hat{\Omega} \cdot \nabla \psi_g(\underline{r}, \hat{\Omega}) + \sigma(\underline{r}) \psi_g(\underline{r}, \hat{\Omega}) \quad (2)$$

$$(S\psi(\underline{r}, \hat{\Omega}))_g = \sum_{g'} \int d\hat{\Omega}' \delta(\underline{r}; \hat{\Omega}', g' \rightarrow \hat{\Omega}, g) \psi_{g'}(\underline{r}, \hat{\Omega}') \quad (3)$$

where the subscript  $g$  denotes the  $g^{\text{th}}$  energy group.



The  $S_N$  approximation discretizes the above equations at  $N$  discrete angular ordinates,  $\hat{\Omega}_n$ , to produce the set

$$L\psi(\underline{r}, \hat{\Omega}_n) = S\psi(\underline{r}, \hat{\Omega}_n) + q(\underline{r}, \hat{\Omega}_n) \quad (4)$$

in which

$$(L\psi(\underline{r}, \hat{\Omega}_n))_g = \hat{\Omega}_n \cdot \nabla \psi_g(\underline{r}, \hat{\Omega}_n) + \sigma(\underline{r}) \psi_g(\underline{r}, \hat{\Omega}_n) \quad (5)$$

and

$$(S\psi(\underline{r}, \hat{\Omega}_n))_g = \sum_{g'} \sum_{m=1}^N \omega_m \delta(\underline{r}; \hat{\Omega}_m, g' \rightarrow \hat{\Omega}_n, g) \psi_{g'}(\underline{r}, \hat{\Omega}_m) \quad (6)$$

where  $\omega_m$  are weights associated with the angular quadrature set  $\{\hat{\Omega}_m\}$  and the sum over  $m$  approximates the integration over  $\hat{\Omega}'$  in (3). Equations (4), (5), and (6) describe the  $S_N$  approximation to the transport equation.

Finite-difference techniques using the diamond difference approximation<sup>8</sup> have been applied which approximate equation (4) to second order in all independent variables in Cartesian geometries and to order  $\Delta r^2/r^2$  in one-dimensional spherical geometry.<sup>31</sup> Applying any method of spatial discretization, the  $S_N$  equations can be written in the matrix form

$$L\underline{\psi} = S\underline{\psi} + \underline{q} \quad (7)$$

where the vectors  $\underline{\psi}$  and  $\underline{q}$  now contain the unknown flux and inhomogeneous source, respectively, in each group and at all mesh points, space and angle. The matrices  $L$  and  $S$  are approximations to the operators  $L$  and  $S$  respectively.



## Outer Iteration

The scattering matrix  $S$  is split as follows

$$S = S_d + S_s + S_u \quad (8)$$

where  $S_d, S_s$ , and  $S_u$  represent down scattering, self or in-group scattering, and up-scattering respectively. The iterative technique

$$(L - S_d - S_s)\underline{\psi}^{j+1} = S_u \underline{\psi}^j + \underline{q} \quad (9)$$

represents the "outer" iteration where  $j$  is the iteration index. This matrix equation is never explicitly solved in transport codes. The matrix  $(L - S_d - S_s)$  is dense and of such large dimension that it is not easily invertible on present day computers. Consequently another splitting is made so that an inner iteration can be conducted within each energy group.

## Inner Iteration

The self or in-group scattering matrix is separated from the left hand side of (9) to operate on the  $k^{\text{th}}$  inner iterate group flux,

$$L_g \psi_g^{j+1, k+1} = S_{sg} \psi_g^{j+1, k} + s_g^{j+1} \quad (10)$$

where the source to the  $g^{\text{th}}$  group is

$$s_g^{j+1} = (S_d \underline{\psi}^{j+1})_g + (S_u \underline{\psi}^j)_g + q_g. \quad (11)$$

In this inner iteration scheme, the first term on the right-hand-side of (11) can be evaluated even though  $\underline{\psi}^{j+1}$  is not





known for groups  $g$  and below, since elements of  $S_d$  corresponding to these groups are zero. The matrices  $L_g$  and  $S_{\delta g}$  in (10) are restrictions of  $L$  and  $S_{\delta}$  to the  $g^{\text{th}}$  group. The vector  $\psi_g^{j+1}$  contains components of  $\underline{\psi}^{j+1}$  corresponding to the  $g^{\text{th}}$  group. The matrix  $L_g$  is triangular and thus easily invertible for typical difference schemes, so  $\underline{\psi}_g^{j+1, k+1}$  can be obtained rapidly from  $\underline{\psi}_g^{j+1, k}$ .<sup>30</sup>

A converged inner iterate solution in each energy group completes one outer iteration. Consequently the outer iterate equation (9) is never solved but its solution is approximated by completing the inner iteration for each group a number of times, each with a source,  $q$ , calculated from previous outer iteration fluxes. For media which do not reproduce neutrons, only one outer iteration is required but for fissioning media, many outer iterations are required.

The problems treated here employ the inner iteration of equation (10) for plane geometry. The specific equations will be developed later.

#### Convergence of $S_N$ Approximation

Early versions of the discrete ordinates equations were used and results compared to those of other methods without regard to their formal convergence properties. Numerical experiments with problems representing physical systems showed that the early (circa late 1950's) time-dependent schemes were stable.<sup>32</sup> Not until 1960 did proof of convergence of the steady-state  $S_N$  approximation appear when Keller<sup>33</sup> proved mean-square convergence of the  $S_N$



approximation to the analytic solution in plane geometry, one-speed, with isotropic scattering for values of  $0 \leq C < 1$  where  $C$  is the mean number of secondary neutrons per collision. At the same time, Wendroff<sup>34</sup> proved pointwise convergence for the same problem for  $C < 1$  and a weighted mean-square convergence for  $C = 1$ . Keller<sup>35</sup> immediately thereafter proved pointwise convergence for the problem for values of  $C$  greater than unity.

Not until 1968 did convergence proofs appear for multidimensional geometries. Madsen<sup>36-38</sup> proved pointwise convergence of the  $S_N$  approximation to the time-independent one-speed angular segmented transport solution in  $x, y$  geometry with vacuum and periodic boundary conditions. In addition he proved that the spatially differenced approximations using the central difference, first-order difference, and diamond difference schemes converge pointwise to the angular  $S_N$  approximation solution in  $x, y$  geometry. Madsen<sup>39</sup> has shown that the  $S_N$  approximation in  $x, y, z$  geometry converges pointwise to the exact solution under certain conditions.

#### Acceleration of Convergence

Current work is being directed toward improved techniques to accelerate convergence of the  $S_N$  algorithm. Clifford<sup>40</sup> gives a lucid account of  $S_N$  running times for shielding problems using various generation digital computers. With present generation IBM/360 series machines, very large two-dimensional problems require 10 to 20 hours



running time. For deep penetration problems in media with  $\sigma^S/\sigma^t$  near unity, Reed<sup>30</sup> states that non-accelerated  $S_N$  methods converge so slowly that they are practically useless.

Several methods have been developed to accelerate inner iteration convergence of the  $S_N$  algorithm. Carlson and Bell<sup>41</sup> proposed a scale factor technique which is used in present standard codes like ANISN. It uses a system-wide neutron conservation principle and iterates until a "false" source is arbitrarily small.<sup>8</sup> Engle<sup>42</sup> found that the scale factor technique accelerates convergence rapidly for absorbing media and near source regions for scattering media but is slow to converge at points many mean free paths away from the source in predominantly scattering media. For the latter problems, the scale factor rapidly approaches unity (even when the group flux solution is far from converged) and thereafter does little to accelerate convergence. Consequently, he proposed a separate scale factor for each space interval which exhibited some success in a one-dimensional 26-group problem. Clancy<sup>43</sup> proposed an outer iteration scaling technique which, when used with inner iteration scaling, accelerates convergence for problems characterized by the presence of significant upscattering.

The acceleration technique often used in one-dimensional problems is that of Chebychev, adapted to transport



approximations by Hageman.<sup>44</sup> It is not as effective in two-dimensional geometries.

The Synthetic Method, first proposed by Kopp<sup>45</sup> and applied by Gelbard<sup>46</sup> has been quite useful in accelerating convergence of the  $S_N$  algorithm in one and two-dimensional problems. This method uses the solution of a diffusion theory approximation to accelerate convergence of the iterative  $S_N$  algorithm.

Another effective method of accelerating convergence is called coarse mesh rebalancing. An early version was suggested by Wachspress<sup>47</sup> for diffusion theory codes. The method has been applied to a transport code, TWOTRAN.<sup>48</sup> A variational rebalancing scheme was devised by Nakamura<sup>49</sup> and applied to the one-dimensional  $S_N$  algorithm.

The most effective acceleration methods proposed to date are the synthetic and coarse mesh rebalance methods. When successful, they lead to tremendous reductions in computing time. Unfortunately, Reed<sup>30</sup> discloses, there are problems for which the use of these acceleration techniques lead to an unstable algorithm. This failure occurs on those problems where it is most necessary to accelerate convergence, namely problems with an optically thick region with scattering ratio near unity. He displays model problems for which the unaccelerated  $S_2$  algorithm requires more than 2600 iterations to converge and the above two methods fail to converge. He also generates parameters which force both methods to converge.





A typical problem for which acceleration techniques are required is neutron propagation through large thicknesses of iron which has a huge scattering resonance at about 25 kev. Devillers<sup>50</sup> compares  $S_N$  codes running times (NIOBE, 20 minutes; ANISN, 8 minutes) to a Monte Carlo code (POKER, 13 minutes) for a one-dimensional multigroup problem. Deep penetration problems in iron have also been solved by  $S_N$  techniques to study the "window" effect for such materials.<sup>51</sup>

Current research is directed toward developing more accurate transport results. Increased emphasis on reactor safety is one factor responsible for this trend. But it is not sufficient to strive for accuracy alone; efficiency or cost must also be considered. Consequently, acceleration techniques play a prominent role in present computer codes. Any technique which contributes to improved efficiency will be incorporated to reduce the expensive computer computational costs.

#### Proposed Investigation

This investigation formulates the angular flux form of the  $S_N$  equations in plane geometry within a mathematical frame which allows an insight into the mechanics of the convergence process. This mathematical formulation leads to sufficiency conditions under which iterative convergence to an exact discretized solution is assured. These conditions include a domain in which some elements of the iteration matrix are allowed to be negative.



The infinity-norm of the iteration matrix is calculated for a problem with a homogeneous isotropically scattering medium. This allows the calculation of an improved convergence criterion. Reed<sup>52</sup> states that the convergence criterion

$$\max_i \left| 1 - \frac{\phi_i^{(k-1)}}{\phi_i^{(k)}} \right| \leq 0.0001$$

where  $\phi_i^{(k)}$  is the  $i^{\text{th}}$  component of the  $k^{\text{th}}$  scalar flux iterate is not, strictly speaking, a measure of the error in the final iterate, since slowly converging methods may meet this test without being close to the exact solution. It is, however, the convergence criterion actually used in most transport codes. This investigation proposes an improved convergence criterion which, along with the demonstrated convergence properties of the  $S_N$  algorithm, guarantees that the fractional iterative error, defined in Chapter II, is arbitrarily small. This is exhibited in Chapter II.

A spatial transform method which accelerates inner iteration convergence for certain  $S_N$  problems is developed in Chapter III. The method is applicable to problems for optically thick media in which the scattering ratio is near unity. The transform renders the angular discretized  $S_N$  equations invariant and places an acceleration parameter in each non-zero matrix element of the iteration matrix such that its norm is reduced. This results in accelerated convergence of the  $S_N$  algorithm.



The reciprocal of the spatial transform is applied to an  $S_N$  problem to reduce the discretization error. This variation of the transform method is applied to a predominantly absorbing medium problem in Chapter IV.

An upper bound is found for the round-off error in the  $S_N$  iterative algorithm describing an inner iteration of a multigroup problem. The expression for this bound provides insight into the reasons why iterative techniques often exhibit smaller roundoff error than competitive matrix inversion methods and how these errors propagate through the iterative process. This exposition is presented in Chapter V.



## CHAPTER II

### DISCRETE ORDINATES AS A METHOD OF SUCCESSIVE APPROXIMATIONS

To analyze the convergence properties of the  $S_N$  algorithm, it is necessary to provide some theoretical background and to show that the algorithm possesses, under certain restrictions, sufficient conditions for convergence.

#### Theoretical Background

The problem to be solved is

$$L\underline{\psi}^* = \underline{q} \quad (1)$$

where  $L$  is a finite dimensional square matrix,  $\underline{\psi}^*$  is the solution vector, and  $\underline{q}$  is the inhomogeneous vector. All vector and matrix elements are real. For the applications considered here,  $L$  is non-singular so equation (1) has a unique solution,  $\underline{\psi}^*$ , for each given  $\underline{q}$ .

Now assume that  $L$  can be split as follows,

$$L = D - E - S. \quad (2)$$

The choice of the splitting is arbitrary but the implication is that  $(D-E)^{-1}$  is an approximation to  $L^{-1}$  but  $(D-E)$  is much simpler to invert than  $L$ . For instance  $(D-E)$  may be chosen such that it is sparse compared to the dense  $L$ .





After splitting  $L$ , equation (1) becomes

$$(D-E) [I - (D-E)^{-1}S] \underline{\psi}^* = \underline{q}$$

or

$$\underline{\psi}^* = [I - (D-E)^{-1}S]^{-1} (D-E)^{-1} \underline{q}$$

where

$$L^{-1} = [I - (D-E)^{-1}S]^{-1} (D-E)^{-1}.$$

Use will now be made of a convergence theorem from Isaacson,<sup>53</sup> which is repeated here. The notation has been modified for convenience to conform to that of the  $S_N$  algorithm used later.

Theorem 1

The geometric series  $\sum_{m=0}^{\infty} [(D-E)^{-1}S]^m$  converges if and only if

$$|| (D-E)^{-1}S || < 1. \quad (3)$$

If  $(D-E)^{-1}S$  is convergent, then  $[I - (D-E)^{-1}S]$  is non-singular and

$$[I - (D-E)^{-1}S]^{-1} = \sum_{m=0}^{\infty} [(D-E)^{-1}S]^m.$$

If the splitting of  $L$  is such that expression (3) is satisfied, the theorem can be invoked to produce

$$L^{-1} = \sum_{m=0}^{\infty} [(D-E)^{-1}S]^m (D-E)^{-1}$$



which is the Neumann series expansion of  $L^{-1}$  and

$$\underline{\psi}^* = \sum_{m=0}^{\infty} [(D-E)^{-1}S]^m (D-E)^{-1}\underline{q} . \quad (4)$$

A consequence of the series expression for  $L^{-1}$  is that

$$||L^{-1}|| \leq \frac{|| (D-E)^{-1} ||}{1 - || (D-E)^{-1} S ||} . \quad (5)$$

Observe that  $||L^{-1}||$  is bounded provided that  $|| (D-E)^{-1} S || < 1$  and that the bound becomes tighter as  $|| (D-E)^{-1} S ||$  approaches zero.

### Iterative Process

On the basis of Theorem 1, Rall<sup>54</sup> constructs an iterative process, called the method of successive approximations, which has

$$\underline{\psi}^{(i+1)} = (D-E)^{-1}S\underline{\psi}^{(i)} + (D-E)^{-1}\underline{q} \quad (6)$$

where  $i$  is an iteration index. This process gives a sequence  $\{\underline{\psi}^{(i)}\}$  of successive approximations which converge to the exact solution  $\underline{\psi}^*$  starting from any initial guess  $\underline{\psi}^{(0)}$ . Equation (6) implies that

$$\underline{\psi}^{(i+1)} = \sum_{m=0}^i [(D-E)^{-1}S]^m (D-E)^{-1}\underline{q} + [(D-E)^{-1}S]^{i+1}\underline{\psi}^{(0)} . \quad (7)$$

Observe that  $\lim_{i \rightarrow \infty} \underline{\psi}^{(i+1)} = \underline{\psi}^*$  since the first term on the right hand side of (7) approaches  $\underline{\psi}^*$  and the second term vanishes due to condition (3).



## Error Estimation

Using equations (4) and (7), it follows that the absolute error, defined by

$$\underline{e}^{(i)} = \underline{\psi}^* - \underline{\psi}^{(i)} \quad (8)$$

is bounded by

$$||\underline{e}^{(i)}|| \leq \frac{||(\underline{D}-\underline{E})^{-1}\underline{S}||^i}{1 - ||(\underline{D}-\underline{E})^{-1}\underline{S}||} \cdot ||(\underline{D}-\underline{E})^{-1}\underline{q}|| \quad (9)$$

for  $\underline{\psi}^{(0)} = 0$ .

This error expression is of little practical value except to illustrate the idea of efficiency. It is desirable to obtain approximations of a given accuracy with the fewest number of iterations. Obviously, more iterations are required to achieve a given accuracy as  $||(\underline{D}-\underline{E})^{-1}\underline{S}||$  approaches unity. Indeed the error is unbounded for  $||(\underline{D}-\underline{E})^{-1}\underline{S}|| = 1$ . But this condition violates expression (3) which guarantees that the series converges to  $\underline{L}^{-1}$ . If  $||(\underline{D}-\underline{E})^{-1}\underline{S}|| \geq 1$ , the convergence of the iterative process is not guaranteed.

## Formulation of $S_N$ Algorithm

The  $S_N$  equations will be derived for an energy group in a multigroup problem applying the following assumptions to the transport equation:

- 1) steady state
- 2) infinite plane geometry with one spatial dimension



- 3) homogeneous medium
- 4) isotropic scattering in the Laboratory Coordinate System
- 5) no reentrant current at the slab boundaries.

The problem may be described by

$$\mu \frac{\partial \psi(x, \mu)}{\partial x} + \sigma^t \psi(x, \mu) = \frac{\sigma^s}{2} \int_{-1}^1 \psi(x, \mu') d\mu' + q(x, \mu) \quad (10)$$

with boundary conditions

$$\psi(0, \mu) = 0 \quad \text{for } \mu > 0 \quad (11a)$$

$$\psi(L, \mu) = 0 \quad \text{for } \mu < 0 \quad (11b)$$

where  $x = 0$  at the left face of the slab and  $x = L$  at the right face of the slab. Equation (10) is the balance equation for the angular flux in a particular energy group. The source term  $q(x, \mu)$  represents neutrons scattered from other energy groups and born within the energy group, either from fission or external sources.

The angular and spatial discretization of equation (10) follows the procedure described by Bell.<sup>55</sup> Alternate formulations by Mynatt,<sup>56</sup> who applies numerical difference methods to the analytic balance equation, and Carlson,<sup>8</sup> who immediately writes a discretized form of the balance equation with unknown coefficients and evaluates them by applying neutron conservation principles, produce the same difference equations in plane geometry. Equation (10) is discretized in direction cosines by approximating it at each





of the  $N$  values of  $\mu_j$  in the quadrature set selected. This gives the  $N$  coupled set of equations

$$\mu_j \frac{d\psi_j(x)}{dx} + \sigma^t \psi_j(x) = \frac{\sigma^s}{2} \sum_{n=1}^N \omega_n \psi_n(x) + q_j(x) \quad (12)$$

$$\text{for } j = 1, 2, \dots, N \text{ where } \mu_{N+1-j} = -\mu_j \quad (13)$$

for  $j = 1, 2, \dots, N/2$ .

A spatial mesh is selected with  $R$  equi-spaced increments providing  $R+1$  space points, including the boundaries, at which  $\psi_j(x)$  is to be approximated. Each increment,  $\Delta$ , is defined by

$$\Delta = x_{k+1} - x_k. \quad (14a)$$

The  $x, \mu$  mesh is described in Figure 1.

The quantity  $\psi_j(x)$  in equation (12) is approximated at each spatial midpoint of the mesh

$$x_{k+1/2} = \frac{x_{k+1} + x_k}{2} \quad (14b)$$

by

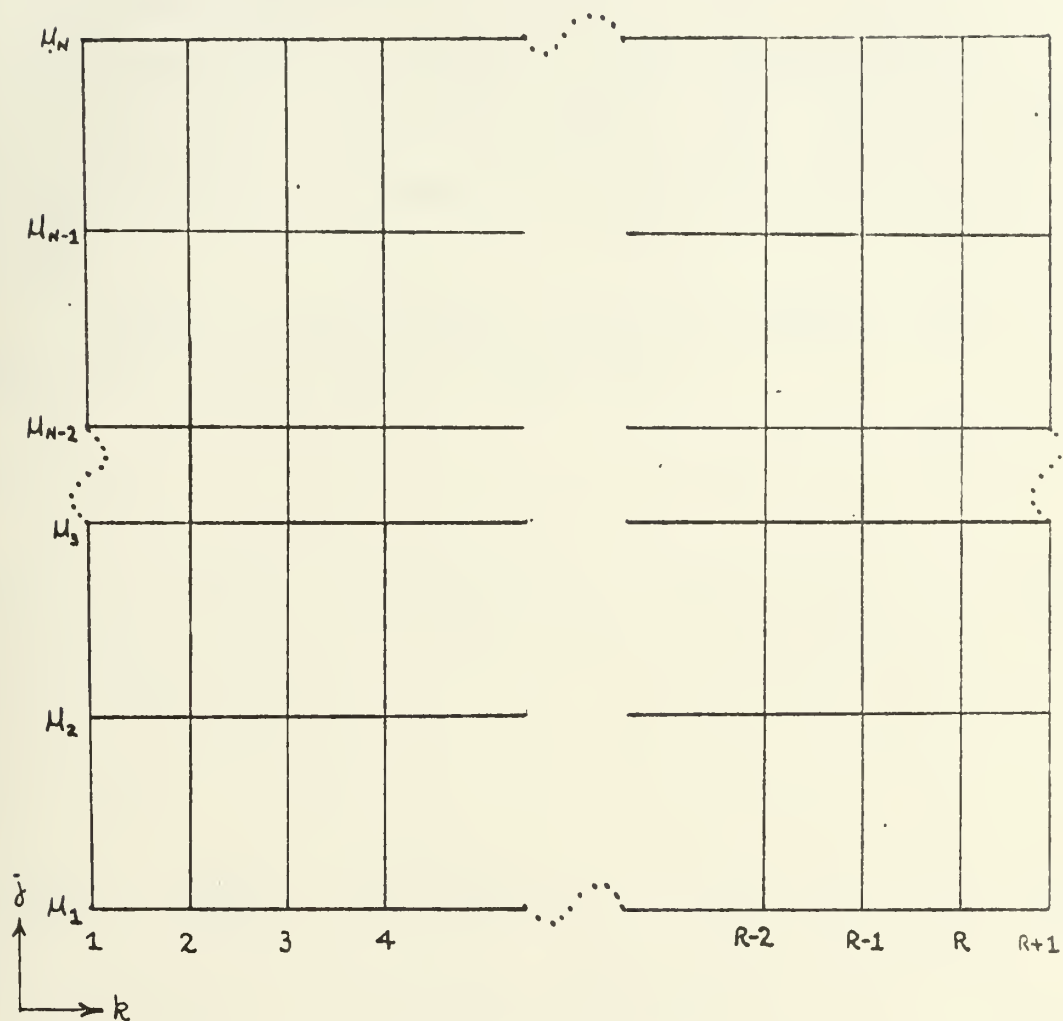
$$\psi_{k+1/2, j} = \frac{\psi_{k+1, j} + \psi_{k, j}}{2} \quad (14c)$$

and the derivative term is approximated by the central difference

$$\left. \frac{d\psi_j(x)}{dx} \right|_{x_{k+1/2}} = \frac{\psi_{k+1, j} - \psi_{k, j}}{\Delta}. \quad (15)$$



FIGURE 2.1  
SPACE-DIRECTION COSINE MESH



Direction set properties:

$$1) \mu_{\frac{N}{2}+j} = -\mu_j, \quad j = 1, 2, \dots, N/2; \quad \mu_j > 0.$$

$$2) \sum_{n=1}^{N/2} \omega_n = 1, \quad \omega_{\frac{N}{2}+j} = \omega_j, \quad j = 1, 2, \dots, \frac{N}{2}; \quad \omega_j > 0.$$



This approximation of  $\psi_j(x)$  by  $\psi_{k,j}$  leads to a type of error called discretization error. Isaacson<sup>53</sup> shows that this approximation is accurate to order  $\Delta^2$ ,  $O(\Delta^2)$ . A desirable strategy is to choose  $\Delta$  small enough that discretization error is reasonably small. This choice is based on a guess of how the solution is expected to vary across the slab.

The above substitutions applied to equation (12) produce the following set of equations.

For  $\mu_j > 0$

$$d_j \psi_{k+1,j} - e_j \psi_{k,j} = \frac{\sigma \Delta}{4} \sum_{n=1}^N w_n (\psi_{k+1,n} + \psi_{k,n}) + q_{k+1/2,j} \quad (16a)$$

$$k = 1, 2, \dots, R.$$

For  $\mu_j < 0$

$$d_j \psi_{k,j} - e_j \psi_{k+1,j} = \frac{\sigma \Delta}{4} \sum_{n=1}^N w_n (\psi_{k+1,n} + \psi_{k,n}) + q_{k+1/2,j} \quad (16b)$$

$$k = R, R-1, \dots, 1. \text{ In these equations}$$

$$d_j = \frac{2|\mu_j| + \Delta \sigma^t}{2\Delta} \quad (16c)$$

and

$$e_j = \frac{2|\mu_j| - \Delta \sigma^t}{2\Delta} \quad (16d)$$

and

$$q_{k+1/2,j} = q(x_{k+1/2}, \mu_j) . \quad (16e)$$

Equations (16) could be arranged in the matrix form



$$L\psi^* = q$$

and the solution  $\psi^*$  found by inverting  $L$ . This procedure is not useful, however, because  $L$  is usually dense and is of such large dimension for practical reactor problems that present day computers do not have sufficient storage capacity to invert such systems. Instead of the above procedure, an iterative technique is used for reactor problems which solves (16) in the following manner.

For  $\mu_j > 0$ ,

$$d_j \psi_{k+1,j}^{(i+1)} - e_j \psi_{k,j}^{(i+1)} = \frac{\sigma}{4} \sum_{n=1}^N w_n (\psi_{k+1,n}^{(i)} + \psi_{k,n}^{(i)}) + q_{k+1/2,j} \quad (17a)$$

and for  $\mu_j < 0$ ,

$$d_j \psi_{k,j}^{(i+1)} - e_j \psi_{k+1,j}^{(i+1)} = \frac{\sigma}{4} \sum_{n=1}^N w_n (\psi_{k+1,n}^{(i)} + \psi_{k,n}^{(i)}) + q_{k+1/2,j} \quad (17b)$$

where  $i$  is an iteration index. These equations are the basic equations describing the  $S_N$  algorithm.

The iterative solution of this system,  $\psi^{(i+1)}$ , approximates the exact matrix solution  $\psi^*$ . The error in this approximation is called iteration error. A practical strategy is to iterate until this error is arbitrarily small.

#### Calculation Sequence

The convention of performing the calculation spatially in the direction of neutron flow, as pointed out by Bell,<sup>55</sup> has been observed in equations (16) and (17).





Consequently, iterative and round-off errors are attenuated rather than amplified as the calculation proceeds. This is observed from the  $S_N$  algorithm in its machine form. That is, for  $\mu_j > 0$

$$\psi_{k+1,j}^{(i+1)} = \frac{e_j}{d_j} \psi_{k,j}^{(i+1)} + \frac{1}{d_j} \left\{ \frac{\sigma^2}{2} \sum_{n=1}^N w_n \psi_{k+1/2,n}^{(i)} + q_{k+1/2,j} \right\} \quad (18a)$$

and for  $\mu_j < 0$

$$\psi_{k,j}^{(i+1)} = \frac{e_j}{d_j} \psi_{k+1,j}^{(i+1)} + \frac{1}{d_j} \left\{ \frac{\sigma^2}{2} \sum_{n=1}^N w_n \psi_{k+1/2,n}^{(i)} + q_{k+1/2,j} \right\}. \quad (18b)$$

The quantities  $\frac{e_j}{d_j}$  are less than unity for all  $j$  so any numerical errors in a particular angular flux value will be attenuated in calculating the neighboring angular flux value. Amplification of these errors would have occurred had the convention not been observed.

#### Iterative Matrix Formulation of the $S_N$ Algorithm

Equations (18) with boundary conditions

$$\psi_{1,j} = 0 \quad \text{for } \mu_j > 0 \quad (18c)$$

$$\psi_{R+1,j} = 0 \quad \text{for } \mu_j < 0 \quad (18d)$$

and an initial guess  $\psi_{k,j}^{(0)} = 0$  for all  $k, j$  is the  $S_N$  machine algorithm for the problem described by equations (10) and (11).

Equations (17) are precisely the same  $S_N$  algorithm expressed in slightly different form. If these equations



for an  $R+1$  by  $N$  mesh (including boundary points) are written so that the solution set is arranged in the following vector order

$$\underline{\psi} = \begin{bmatrix} \psi_{2,1} \\ \psi_{3,1} \\ \vdots \\ \psi_{R+1,1} \\ \psi_{2,2} \\ \psi_{3,2} \\ \vdots \\ \psi_{R+1,2} \\ \vdots \\ \psi_{R+1,N/2} \\ \psi_{R,N/2+1} \\ \psi_{R-1,N/2+1} \\ \vdots \\ \psi_{1,N/2+1} \\ \psi_{R,N/2+2} \\ \psi_{R-1,N/2+2} \\ \vdots \\ \psi_{1,N/2+2} \\ \vdots \\ \psi_{1,N} \end{bmatrix}, \quad (19)$$

which has dimension  $R \cdot N$ , then equations (17) describe the matrix system

$$(D-E)\underline{\psi}^{(i+1)} = S \underline{\psi}^{(i)} + \underline{q}. \quad (20)$$



The matrix (D-E) is block diagonal of the form

$$\begin{bmatrix} B_1 & & & \\ & B_2 & & \\ & & \ddots & \\ & & & B_N \end{bmatrix} \quad (21)$$

where each block is an  $R$  by  $R$  submatrix.  $R$  is the number of spatial increments in the mesh. There are  $N$  such blocks.

Each block  $B_j$  has the lower bi-diagonal form

$$\begin{bmatrix} d_j & & & & & & \\ -e_j & d_j & & & & & \\ & -e_j & d_j & & & & \\ & & \ddots & \ddots & \ddots & & \\ & & & \ddots & \ddots & \ddots & \\ & & & & \ddots & \ddots & \\ & & & & & -e_j & d_j \end{bmatrix} \quad (22)$$

where  $j$  is the index belonging to  $\mu_j$  in the direction set from which  $e_j$  and  $d_j$  are calculated by equations (16c) and (16d).



The  $S$  matrix also has a regular block structure of the form

$$S = \begin{array}{cccccc} \begin{array}{cc} S_{BD_1} & S_{BD_2} \\ S_{BD_1} & S_{BD_2} \\ \vdots & \vdots \end{array} & \cdots & \begin{array}{cc} S_{BD_{N/2}} & S_{CD_{\frac{N}{2}+1}} \\ S_{BD_{N/2}} & S_{CD_{\frac{N}{2}+1}} \\ \vdots & \vdots \end{array} & \cdots & \begin{array}{cc} S_{CD_{N-1}} & S_{CD_N} \\ S_{CD_{N-1}} & S_{CD_N} \\ \vdots & \vdots \end{array} \\ \begin{array}{cc} S_{BD_1} & S_{BD_2} \\ S_{CD_1} & S_{CD_2} \\ \vdots & \vdots \end{array} & \cdots & \begin{array}{cc} S_{BD_{N/2}} & S_{CD_{\frac{N}{2}+1}} \\ S_{CD_{N/2}} & S_{BD_{\frac{N}{2}+1}} \\ \vdots & \vdots \end{array} & \cdots & \begin{array}{cc} S_{CD_{N-1}} & S_{CD_N} \\ S_{BD_{N-1}} & S_{BD_N} \\ \vdots & \vdots \end{array} \\ \begin{array}{cc} S_{CD_1} & S_{CD_2} \\ S_{CD_1} & S_{CD_2} \\ \vdots & \vdots \end{array} & \cdots & \begin{array}{cc} S_{CD_{N/2}} & S_{BD_{\frac{N}{2}+1}} \\ S_{CD_{N/2}} & S_{BD_{\frac{N}{2}+1}} \\ \vdots & \vdots \end{array} & \cdots & \begin{array}{cc} S_{BD_{N-1}} & S_{BD_N} \\ S_{BD_{N-1}} & S_{BD_N} \\ \vdots & \vdots \end{array} \end{array} \quad (23)$$

where the notation  $S_{CD}$  and  $S_{BD}$  distinguishes the form of the block submatrix and the subscript denotes the index belonging to all elements in a particular block. The  $S$  matrix has certain block regularities listed below:

- 1) The same index appears in each column of blocks.
- 2) Each block is an  $R$  by  $R$  submatrix of  $S$ .
- 3) There are  $N$  blocks in each row and column of blocks.
- 4) The upper right and lower left quadrants of  $S$  are composed of blocks, each with form  $S_{CD}$ .
- 5) The upper left and lower right quadrants of  $S$  are composed of blocks, each with the form  $S_{BD}$ .





The block  $S_{BD_i}$  form is

(24)



which will be called upper cross bidiagonal. The matrix elements are given by (25).

### Inverting the Matrix (D-E)

Due to the simple block form of (D-E) and the fact that each block is lower bidiagonal, see (21) and 22), its inverse is of a simple form. In fact  $(D-E)^{-1}$  is of the block form

$$\begin{array}{c}
 \boxed{B_1^{-1}} \\
 \begin{array}{c} \circ \end{array} \\
 \boxed{B_2^{-1}} \\
 \begin{array}{c} \cdot \\ \cdot \\ \cdot \\ \cdot \end{array} \\
 \begin{array}{c} \circ \end{array} \\
 \boxed{B_N^{-1}}
 \end{array} \quad (27)$$

where each block,  $B_i$ , of (21) is inverted individually and placed in the same position in  $(D-E)^{-1}$  that it held in (D-E).

Each block  $B_i^{-1}$  can easily be calculated from (22) using the method described in Wylie.<sup>57</sup>  $B_i^{-1}$  has the form



$$\begin{array}{l}
 k^{th} \text{ row} \\
 \left[ \begin{array}{ccccccc}
 \frac{1}{d_i} & & & & & & \\
 \frac{e_i}{d_i^2} & \frac{1}{d_i} & & & & & \bigcirc \\
 \frac{e_i^2}{d_i^3} & \frac{e_i}{d_i^2} & \frac{1}{d_i} & & & & \\
 \vdots & \vdots & \vdots & \ddots & & & \\
 \frac{e_i^{k-1}}{d_i^k} & \frac{e_i^{k-2}}{d_i^{k-1}} & \frac{e_i^{k-3}}{d_i^{k-2}} & & & & \\
 \vdots & \vdots & \vdots & \ddots & & & \\
 \frac{e_i^{R-1}}{d_i^R} & \frac{e_i^{R-2}}{d_i^{R-1}} & \frac{e_i^{R-3}}{d_i^{R-2}} & \dots & \dots & \frac{e_i^2}{d_i^3} & \frac{e_i}{d_i^2} & \frac{1}{d_i}
 \end{array} \right] = B_i^{-1}
 \end{array}
 \quad (28)$$

which is lower triangular with elements given by (16c) and (16d).

Since  $(D-E)^{-1}$  and  $S$  are now known, equation (20) can be operated on by  $(D-E)^{-1}S$  to obtain

$$\underline{\psi}^{(i+1)} = (D-E)^{-1}S \underline{\psi}^{(i)} + (D-E)^{-1} \underline{q}. \quad (29)$$

The matrix  $(D-E)^{-1}S$  is called the iteration matrix and can be determined from (23), (24), (26), (27), and (28).  $(D-E)^{-1}S$  can be formed by multiplying (27) onto (23) block by block: That is, due to the block diagonal form of  $(D-E)^{-1}$ ,  $(D-E)^{-1}S$  is formed by matrix multiplying  $B_i^{-1}$  onto each block in the  $i^{th}$  row of blocks in  $S$ . That is,



$$(D-E)^{-1}S = \begin{array}{c} \begin{array}{|c|c|c|c|c|c|c|} \hline B_1^{-1}S_{BD_1} & B_1^{-1}S_{BD_2} & \dots & B_1^{-1}S_{BD_{\frac{N}{2}}} & B_1^{-1}S_{CD_{\frac{N}{2}+1}} & \dots & B_1^{-1}S_{CD_{N-1}} & B_1^{-1}S_{CD_N} \\ \hline B_2^{-1}S_{BD_1} & B_2^{-1}S_{BD_2} & \dots & B_2^{-1}S_{BD_{\frac{N}{2}}} & B_2^{-1}S_{CD_{\frac{N}{2}+1}} & \dots & B_2^{-1}S_{CD_{N-1}} & B_2^{-1}S_{CD_N} \\ \hline \vdots & \vdots & & \vdots & \vdots & & \vdots & \vdots \\ \hline B_N^{-1}S_{BD_1} & B_N^{-1}S_{BD_2} & \dots & B_N^{-1}S_{BD_{\frac{N}{2}}} & B_N^{-1}S_{CD_{\frac{N}{2}+1}} & \dots & B_N^{-1}S_{CD_{N-1}} & B_N^{-1}S_{CD_N} \\ \hline B_N^{-1}S_{CD_1} & B_N^{-1}S_{CD_2} & \dots & B_N^{-1}S_{CD_{\frac{N}{2}}} & B_N^{-1}S_{BD_{\frac{N}{2}+1}} & \dots & B_N^{-1}S_{BD_{N-1}} & B_N^{-1}S_{BD_N} \\ \hline \vdots & \vdots & & \vdots & \vdots & & \vdots & \vdots \\ \hline B_N^{-1}S_{CD_1} & B_N^{-1}S_{CD_2} & \dots & B_N^{-1}S_{CD_{\frac{N}{2}}} & B_N^{-1}S_{BD_{\frac{N}{2}+1}} & \dots & B_N^{-1}S_{BD_{N-1}} & B_N^{-1}S_{BD_N} \\ \hline \end{array} \end{array} \quad (30)$$

where each block is of dimension  $R$  by  $R$ . There are  $N$  by  $N$  such blocks in  $(D-E)^{-1}S$ . The following regularities in the block structure of  $(D-E)^{-1}S$  are observed:

- 1) Each block in the  $i^{th}$  row of blocks has  $B_i^{-1}$  as an operator where  $i$  is the index for  $\mu_i$ .
- 2) Each block in the  $j^{th}$  column of blocks has either  $S_{BD_j}$  or  $S_{CD_j}$  as an operator where  $j$  is the index on  $\omega_j$ .
- 3) The upper-right and lower-left quadrants of  $(D-E)^{-1}S$  are composed of blocks, each of which includes an operator of the form  $S_{CD_j}$ .
- 4) The upper left and lower right quadrants of  $(D-E)^{-1}S$  are composed of blocks, each of which includes an operator of the form  $S_{BD_j}$ .

The matrix form of each block of  $(D-E)^{-1}S$  is one of two kinds,  $B_i S_{BD_j}$  or  $B_i S_{CD_j}$ .

The form of  $B_i S_{BD_j}$  is





$$\begin{array}{c}
 (\omega_j) \frac{1}{j} \\
 \hline
 \begin{array}{|c|c|c|c|c|c|c|}
 \hline
 \begin{array}{c} \frac{e_i}{d_i^2} + \frac{1}{d_i} \\ \frac{e_i^2}{d_i^3} + \frac{e_i}{d_i^2} \\ \vdots \\ \frac{e_i^{R-3}}{d_i^{R-2}} + \frac{e_i^{R-4}}{d_i^{R-3}} \\ \frac{e_i^{R-2}}{d_i^{R-1}} + \frac{e_i^{R-3}}{d_i^{R-2}} \\ \frac{e_i^{R-1}}{d_i^R} + \frac{e_i^{R-2}}{d_i^{R-1}} \end{array} &
 \begin{array}{c} \frac{1}{d_i} \\ \frac{e_i}{d_i^2} + \frac{1}{d_i} \\ \vdots \\ \frac{e_i^{R-4}}{d_i^{R-3}} + \frac{e_i^{R-5}}{d_i^{R-4}} \\ \frac{e_i^{R-3}}{d_i^{R-2}} + \frac{e_i^{R-4}}{d_i^{R-3}} \\ \frac{e_i^{R-2}}{d_i^{R-1}} + \frac{e_i^{R-3}}{d_i^{R-2}} \end{array} &
 \begin{array}{c} \frac{1}{d_i} \\ \frac{1}{d_i} \\ \vdots \\ \frac{e_i^{R-5}}{d_i^{R-4}} + \frac{e_i^{R-6}}{d_i^{R-5}} \\ \frac{e_i^{R-4}}{d_i^{R-3}} + \frac{e_i^{R-5}}{d_i^{R-4}} \\ \frac{e_i^{R-3}}{d_i^{R-2}} + \frac{e_i^{R-4}}{d_i^{R-3}} \end{array} &
 \begin{array}{c} \vdots \\ \vdots \\ \vdots \\ \vdots \\ \vdots \\ \vdots \end{array} &
 \begin{array}{c} \circ \\ \vdots \\ \vdots \\ \vdots \\ \vdots \\ \vdots \end{array} &
 \begin{array}{c} \circ \\ \vdots \\ \vdots \\ \vdots \\ \vdots \\ \vdots \end{array} &
 \begin{array}{c} \frac{1}{d_i} \\ \frac{e_i}{d_i^2} + \frac{1}{d_i} \\ \frac{e_i^2}{d_i^3} + \frac{e_i}{d_i^2} \\ \frac{e_i}{d_i^2} + \frac{1}{d_i} \\ \frac{e_i^2}{d_i^3} + \frac{e_i}{d_i^2} \\ \frac{e_i}{d_i^2} + \frac{1}{d_i} \end{array} \\
 \hline
 \end{array}
 \end{array}
 = B_i^{-1} S_{SD_j} \quad (31)$$

where  $e_i$  and  $d_i$  are values of equations (16c) and (16d) evaluated at  $|\mu_i|$  and  $\omega_j$  is the  $j^{th}$  weight in the quadrature set.

The form of  $B_i^{-1} S_{SD_j}$  is







This discovery, however, allows the  $S_N$  algorithm to be classified as a method of successive approximation which provides a mathematical description of its convergence properties and error analysis. That is, equation (29) is precisely the same as (6). Consequently, properties previously discussed for the method of successive approximations apply to the  $S_N$  method if the conditions of Theorem 1 are met. Before this is attempted, it is necessary to show that the norm of the iteration matrix can be calculated for the  $S_N$  problem previously described.

Calculation of  $|| (D-E)^{-1} S ||$

The norm imposed upon the system is the infinity norm, defined for a vector by

$$|| \underline{\psi} ||_{\infty} = \max_k |\psi_k| . \quad (33)$$

Obviously, this norm is conveniently chosen for pointwise error analysis. Isaacson<sup>53</sup> shows that for a matrix,  $A$ ,

$$|| A ||_{\infty} = \max_i \sum_j |a_{ij}| , \quad (34)$$

that is, the maximum row sum of absolute values of the matrix elements. From this point, the above definitions will hold for the norms simply denoted by  $|| \quad ||$ .

The row sum of  $(D-E)^{-1} S$ , described by (30), (31), and (32) will be a row sum in a row of blocks which comprise  $(D-E)^{-1} S$ . Since each row of blocks has the same form, it is sufficient to sum a row of blocks and pick the



row from the block sum which gives the maximum row sum of absolute values for  $(D-E)^{-1}S$ .

Due to the ordering of the direction set,

$$w_{\frac{N}{2}+j} = w_j \quad (35)$$

for  $j = 1, 2, \dots, N/2$ . A property of the direction set is that

$$\sum_{j=1}^{N/2} w_j = 1. \quad (36)$$

Consequently a block row sum of  $(D-E)^{-1}S$  can be collapsed by taking

$$\begin{aligned} & B_i^{-1}S_{BD_1} + B_i^{-1}S_{BD_2} + \dots + B_i^{-1}S_{CD_N} = \\ &= (B_i^{-1}S_{BD_1} + B_i^{-1}S_{CD_{\frac{N}{2}+1}}) + (B_i^{-1}S_{BD_2} + B_i^{-1}S_{CD_{\frac{N}{2}+2}}) + \dots + (B_i^{-1}S_{BD_{\frac{N}{2}}} + B_i^{-1}S_{CD_N}) \\ &= \frac{\sigma^\Delta}{4} \left\{ w_1 (B_i^{-1}S_{BD} + B_i^{-1}S_{CD}) + w_2 (B_i^{-1}S_{BD} + B_i^{-1}S_{CD}) + \dots + w_{\frac{N}{2}} (B_i^{-1}S_{BD} + B_i^{-1}S_{CD}) \right\} \\ &= \frac{\sigma^\Delta}{4} (w_1 + w_2 + \dots + w_{\frac{N}{2}}) (B_i^{-1}S_{BD} + B_i^{-1}S_{CD}) \\ &= \frac{\sigma^\Delta}{4} (B_i^{-1}S_{BD} + B_i^{-1}S_{CD}) \end{aligned} \quad (37)$$

where  $B_i^{-1}S_{BD} + B_i^{-1}S_{CD}$  = sum of the matrix parts of equations (31) and (32).

It is observed from (37), (31), and (32) that the sum of absolute values of the elements of each successive row include all elements of the preceding row plus a positive





quantity. This is true of all row sums except the last.

The last row sum is equal to

$$\frac{\sigma^{\Delta}}{4} \left[ 3 \left( \left| \frac{1}{d_i} \right| + \left| \frac{e_i^{R-1}}{d_i^R} \right| \right) + 4 \left( \left| \frac{e_i}{d_i^2} \right| + \left| \frac{e_i^2}{d_i^3} \right| + \cdots + \left| \frac{e_i^{R-2}}{d_i^{R-1}} \right| \right) \right]. \quad (38)$$

The next to last row sum is equal to

$$\frac{\sigma^{\Delta}}{4} \left[ 3 \left| \frac{e_i^{R-2}}{d_i^{R-1}} \right| + 4 \left( \left| \frac{1}{d_i} \right| + \left| \frac{e_i}{d_i^2} \right| + \left| \frac{e_i^2}{d_i^3} \right| + \cdots + \left| \frac{e_i^{R-3}}{d_i^{R-2}} \right| \right) \right]. \quad (39)$$

The last row sum is the maximum if,

$$\left| \frac{e_i^{R-2}}{d_i^{R-1}} \right| + 3 \left| \frac{e_i^{R-1}}{d_i^R} \right| > \left| \frac{1}{d_i} \right| \quad \text{or if} \quad \left| \frac{e_i}{d_i} \right|^{R-2} + 3 \left| \frac{e_i}{d_i} \right|^{R-1} > 1. \quad (40)$$

Even if  $\Delta, \sigma^{\Delta}$ , and  $|\mu_i|$  were adjusted so that  $e_i < 0$ , the quotient  $\frac{|e_i|}{d_i}$  is less than unity because  $|e_i| < d_i$  for all  $i$ . Consequently, for systems with large  $R$ , the next to last row sum is the maximum.

Now the block row sum must be picked from all possibilities. The index  $i$  for which expressions (38) and (39) are maximum can be determined from equations (16c) and (16d).

The quantity

$$\frac{|e_i|}{d_i} = \frac{\left| 1 - \frac{\Delta \sigma^{\Delta}}{2 |\mu_i|} \right|}{1 + \frac{\Delta \sigma^{\Delta}}{2 |\mu_i|}}$$

attains its smallest value for a given  $\Delta$  and  $\sigma^{\Delta}$  when  $|\mu_i|$  is the minimum in the quadrature set  $\{\mu_j\}$ . Also



$\frac{1}{\bar{d}_i} = \frac{2\Delta}{2|\mu_i| + \Delta\sigma^t}$  is a maximum for the same  $|\mu_i|$ . The latter factor dominates, however, in the norm determination. Therefore the norm is calculated by using the minimum absolute ordinate value in the set  $\{\mu_j\}$ . Consequently

$$||(\mathbf{D}-\mathbf{E})^{-1}\mathbf{S}|| \leq \left\{ \begin{array}{ll} \left[ \frac{\sigma^\delta}{4} \left[ \frac{3}{\bar{d}_i} \left( 1 + \left| \frac{e_i}{\bar{d}_i} \right|^{R-1} \right) + \frac{4}{\bar{d}_i} \left( \left| \frac{e_i}{\bar{d}_i} \right| + \left| \frac{e_i}{\bar{d}_i} \right|^2 + \dots + \left| \frac{e_i}{\bar{d}_i} \right|^{R-2} \right) \right] \right] & \text{if } \left| \frac{e_i}{\bar{d}_i} \right|^{R-2} + 3 \left| \frac{e_i}{\bar{d}_i} \right|^{R-1} > 1 \\ \left[ \frac{\sigma^\delta}{4} \left[ \frac{3}{\bar{d}_i} \left| \frac{e_i}{\bar{d}_i} \right|^{R-2} + \frac{4}{\bar{d}_i} \left( 1 + \left| \frac{e_i}{\bar{d}_i} \right| + \left| \frac{e_i}{\bar{d}_i} \right|^2 + \dots + \left| \frac{e_i}{\bar{d}_i} \right|^{R-3} \right) \right] \right] & \text{otherwise} \end{array} \right\} \quad (41)$$

where  $i$  is the index for the minimum absolute ordinate value in the set  $\{\mu_j\}$ . The latter value is appropriate for large  $R$ . Observe that equality occurs when  $e_i \geq 0$ .

For a given  $\Delta, \sigma^t, \sigma^\delta$ ,  $|\mu_i|_{\min}$ , and  $R$  the infinity-norm of the iteration matrix can be calculated by (41). It is obvious that the norm is bounded since  $\frac{|e_i|}{\bar{d}_i} < 1$  and  $\frac{1}{\bar{d}_i}$  is bounded for any finite dimensional system.

Observe that, for a fixed  $\Delta, \sigma^t$ , and  $|\mu_i|_{\min}$ , the coefficients  $e_j$  and  $\bar{d}_j$  are fixed. In this case the norm decreases linearly with  $\sigma^\delta$ . Consequently the norm of the iteration matrix is small for problems involving primarily absorbing media and large near unity for predominantly scattering media. This results in rapid convergence to an acceptable iterative error for absorbing media and slow convergence to the same level of error for predominantly scattering media. This behavior is predicted by equation (9). It will be verified experimentally later.



# Sufficient Conditions for Convergence of $S_N$

Equation (41) will be used to provide sufficient conditions to guarantee that  $|| (D-E)^{-1} S || < 1$  in order that the  $S_N$  algorithm can meet the conditions of Theorem 1. For large  $R$ ,  $|| (D-E)^{-1} S ||$  is evaluated by the second expression in (41), which can be rewritten

$$|| (D-E)^{-1} S || \leq \frac{\sigma^\delta}{4d_i} \left[ 4 \left( \frac{1-\beta^{R-1}}{1-\beta} \right) - \beta^{R-2} \right] \quad (42)$$

where  $0 \leq \beta = \frac{|e_i|}{d_i} < 1$  . (43)

For large  $R$  the terms  $\beta^{R-1}$  and  $\beta^{R-2}$  are insignificant and could be neglected. But since

$$4 \left( \frac{1-\beta^{R-1}}{1-\beta} \right) - \beta^{R-2} < \frac{4}{1-\beta} ,$$

imposing the condition

$$\frac{\sigma^\delta}{d_i} \left( \frac{1}{1-\beta} \right) < 1 \quad (44)$$

will guarantee that  $|| (D-E)^{-1} S || < 1$  without seriously loosening the resulting bounds on  $\Delta$ .

From (16c), (16d), and (43), expression (44) becomes

$$d_i > \sigma^\delta + |e_i|$$

or

$$2|\mu_i|_{min} + \Delta\sigma^t > \Delta\sigma^\delta + \left| 2|\mu_i|_{min} - \Delta\sigma^t \right| . \quad (45)$$



This inequality provides the sufficiency conditions for convergence of the  $S_N$  algorithm.

Suppose the problem is defined so that  $\sigma^\delta, \sigma^t$ , and  $|\mu_i|_{min}$  have been selected and it is desired to impose a sufficient condition on the choice of  $\Delta$  so that (45) is satisfied. Then the condition  $|| (D-E)^{-1} S || < 1$  is satisfied.

Suppose further that  $\Delta \sigma^t > 2|\mu_i|_{min}$  so that  $e_i < 0$ . Then (45) becomes

$$2|\mu_i|_{min} + \Delta \sigma^t > 2\Delta \sigma^\delta + \Delta \sigma^t - 2|\mu_i|_{min}$$

or

$$\Delta < \frac{2|\mu_i|_{min}}{\sigma^\delta} . \quad (46)$$

This imposes a limit on the negativity of the elements  $e_i$ .

If  $\Delta \sigma^t$  had been chosen equal to  $2|\mu_i|_{min}$ . Then  $\beta=0$  in (42) and  $\frac{\sigma^\delta}{\sigma^t} < 1$  is a sufficient condition for  $|| (D-E)^{-1} S || < 1$ . But this leads to the inequality

$$\Delta < \frac{2|\mu_i|_{min}}{2\sigma^\delta - \sigma^t} . \quad \text{But } \Delta = \frac{2|\mu_i|_{min}}{\sigma^t}$$

so the inequality becomes  $\frac{1}{\sigma^t} < \frac{1}{2\sigma^\delta - \sigma^t}$  or  $\sigma^\delta < \sigma^t$ . Consequently  $|| (D-E)^{-1} S || < 1$  in this case if

$$0 \leq \frac{\sigma^\delta}{\sigma^t} < 1 . \quad (47)$$





Finally, suppose  $\Delta\sigma^t < 2|\mu_i|_{min}$  is selected. This choice guarantees that  $e_j$  and  $d_j$  are positive for all  $j$ , hence  $(D-E)^{-1}S$  and  $(D-E)^{-1}$  are positive operators. Expression (45) is then

$$2|\mu_i|_{min} + \Delta\sigma^t > 2\Delta\sigma^s + 2|\mu_i|_{min} - \Delta\sigma^t$$

or

$$\frac{\sigma^s}{\sigma^t} < 1. \quad (48)$$

Consequently,  $|| (D-E)^{-1}S || < 1$  for all physical problems with this choice of  $\Delta$ .

Properties of  $(D-E)^{-1}$

The matrix  $(D-E)$  exists in the construction given by (21) and (22). It is a linear operator due to its construction from the discretized linear equations (17). It is a bounded operator since

$$|| (D-E) || = d_i + |e_i|$$

which is bounded for all finite values of  $\sigma^s, \sigma^t, |\mu_i|_{min}$ , and  $\Delta$ .

The matrix  $(D-E)^{-1}$  exists if  $\det(D-E)$  is non-zero. From equations (21) and (22)

$$\det(D-E) = (d_1 d_2 \dots d_N)^R$$

and since  $d_j > 0$  for all  $j$ ,  $\det(D-E) \neq 0$ .



All conditions of Theorem 1 are met by the  $S_N$  algorithm if the sufficiency conditions listed in Table I are met by the problem parameters. If these conditions are met,  $|| (D-E)^{-1} S || < 1$  and the  $S_N$  algorithm converges to  $\underline{\psi}^*$ , the exact solution of the discretized set of equations.

TABLE I  
SUFFICIENCY CONDITIONS FOR CONVERGENCE OF  $S_N$

Possible Choice For $\Delta$	Value of $e_i$	Bound on $\Delta$ to Meet Sufficiency Condition	Values of $\sigma^s/\sigma^t$ for Which $S_N$ Algorithm Converges
$\Delta > \frac{2 \mu_i _{min}}{\sigma^t}$	Negative	$\Delta < \frac{2 \mu_i _{min}}{\sigma^s}$	$0 \leq \frac{\sigma^s}{\sigma^t} < 1$
$\Delta = \frac{2 \mu_i _{min}}{\sigma^t}$	0	—	$0 \leq \frac{\sigma^s}{\sigma^t} < 1$
$\Delta < \frac{2 \mu_i _{min}}{\sigma^t}$	Positive	$\Delta < \frac{2 \mu_i _{min}}{\sigma^t}$	$0 \leq \frac{\sigma^s}{\sigma^t} < 1$

The above table can be summarized by stating that the sufficiency condition is met for any  $\Delta$  provided that  $\sigma^s < \sigma^t$  or  $\frac{2|\mu_i|_{min}}{\Delta}$ , whichever is smaller.

The consequences of the  $S_N$  algorithm meeting the sufficiency conditions for convergence are that expressions (1) through (9) can be used to study its convergence and iteration error properties.



## Positivity

Positivity of the solution of the  $S_N$  equations for positive source and non-negative boundary conditions is desirable because it is a numerical approximation to a non-negative physical quantity. In practice the  $S_N$  algorithm has produced negative solutions.<sup>8</sup> One-dimensional discrete ordinates codes such as ANISN<sup>58</sup> and DTF-IV<sup>59</sup> have flux fix-up routines incorporated so that negative solution values are not allowed to occur. This strategy, although of practical merit, is not mathematically rigorous. The effect of these arbitrary fix-ups on the iteration error is not clear. Lathrop<sup>60</sup> investigated various two-dimensional difference schemes and found that the quest for positivity is made at the expense of accuracy and efficiency of convergence. Bell<sup>55</sup> points out that the  $S_N$  difference equations may lead to negative solution values since they do not correspond to a positive operator.

The preceding section revealed that sufficiency conditions for convergence of the  $S_N$  algorithm can be met which allow the iteration matrix to possess negative matrix elements. But convergence to the exact solution cannot be guaranteed if  $\Delta$  is chosen so that  $\Delta > \frac{2|\mu_i|_{min}}{\sigma_d}$ . Consequently, there is a limit on the negativity of some of the elements of  $(D-E)^{-1}S$  if the theory is to be invoked to guarantee convergence.

For computational economy reasons it is desirable to choose  $\Delta$  as large as possible. For the problem



previously described, however,  $\Delta < \frac{2|\mu_i|_{min}}{\sigma^4}$  imposes an absolute upper bound on  $\Delta$ , above which the sufficient condition for convergence is not met. If this bound on  $\Delta$  is observed, it is reasonable to assume that the approximate solution  $\underline{\psi}^{(i)}$  will be non-negative if  $i$  is large enough even though initial iterates may have some negative components. This is because  $\underline{\psi}^*$  is expected to be a non-negative vector due to its approximation of  $\psi_j(x)$  which is non-negative by its physical interpretation and  $\underline{\psi}^{(i)}$  approaches  $\underline{\psi}^*$  as  $i$  becomes large. This is true even though the theory of positive operators, which is used successfully in multi-group diffusion theory,<sup>47</sup> is not applicable in this instance. Of course no guarantee exists that  $\underline{\psi}^*$ , the discrete approximation to  $\psi_j(x)$  is non-negative. Numerical experiments by the author confirm that it is for uniform and first collision sources when the sufficiency conditions are met.

If  $\Delta$  is chosen so that  $\Delta < \frac{2|\mu_i|_{min}}{\sigma^4}$ , however,  $(D-E)^{-1}S$  and  $(D-E)^{-1}$  are non-negative matrix operators which guarantee a non-negative approximation  $\underline{\psi}^{(i)}$  for all  $i$ .

### Necessary Conditions

The previously discussed conditions are not necessary for the  $S_N$  iterative process to terminate based upon fractional differences reaching an arbitrarily small value. Indeed termination of the  $S_N$  algorithm iterative process has been observed by this investigator for choices of





$\Delta \gg \frac{2|\mu_i|_{min}}{\sigma^b}$  for which  $|| (D-E)^{-1}S || \gg 1$ . For some sources, e.g. uniform source, convergence to a positive solution vector occurred. For other sources, e.g. first collision source, the solution vector contained negative components. It is doubtful whether this process can accurately be called convergence since the nature of the resulting solution is not clearly defined.

Even if  $\Delta$  is chosen so that  $\Delta > \frac{2|\mu_i|_{max}}{\sigma^t}$ , in which case all  $e_j$  are negative,  $(D-E)^{-1}S$  contains even and odd powers of  $e_i/d_i$ . Consequently, the iteration matrix is not wholly negative. In this instance the  $S_N$  algorithm may or may not converge to a non-positive solution depending upon the source distribution. For these cases, where some elements of the solution are negative, doubt exists as to the nature of the solution.

It is not clear that necessary conditions on  $\Delta$  exist for convergence of the  $S_N$  algorithm. It is clear, however, that a solution exists if the sufficiency conditions are met and that these conditions allow a limited amount of negativity for the iteration matrix. For the numerical problems previously cited, these solutions are positive.



Effect of  $\Delta$  on  $|| (D-E)^{-1} S ||$

Figure 2.2 reveals the effect of  $\Delta$  on  $|| (D-E)^{-1} S ||$  for the following problem parameters:

$$\text{slab width} = 10.0 \text{ cm}$$

$$\sigma^t = 1.0 \text{ cm}^{-1}$$

$$\sigma^s = 0.9 \text{ cm}^{-1}$$

$$|\mu_i|_{min} = 0.23862$$

As  $R$  (the number of spatial increments) decreases,  $\Delta$

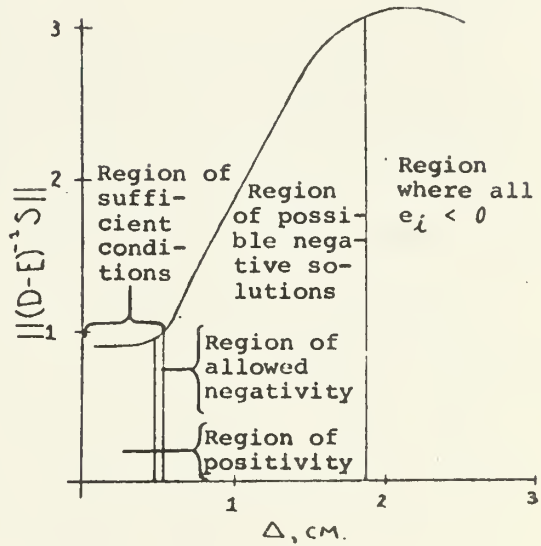
becomes larger and  $|| (D-E)^{-1} S ||$  increases. In the region where  $\Delta$  meets the sufficiency conditions,  $|| (D-E)^{-1} S || < 1$  and convergence of  $S_N$  to the exact matrix solution is assured. A small part of this region allows negative elements in  $(D-E)^{-1} S$ .

In the region where  $|| (D-E)^{-1} S || > 1$ , termination of the iterative process may occur. Solution vectors may be positive or partially negative depending upon the source distribution. This region should be avoided for practical problems unless other evidence is available that the solution has validity.

Effect of Quadrature Set on  $|| (D-E)^{-1} S ||$

Expression (9) reveals that the iterative error is less tightly bounded as  $|| (D-E)^{-1} S ||$  increases towards unity. This means that more iterations are required to

FIGURE 2.2  
NORM BEHAVIOR WITH  $\Delta$





reach a specified accuracy. Equation (41) shows that  $|| (D-E)^{-1} S ||$  increases for fixed  $\Delta, \sigma^x, \sigma^y$ , as the ordinate  $|\mu_i|_{min}$  decreases. This is because  $\frac{1}{d_i}$  grows larger and  $|e_i|/d_i$  diminishes as  $\Delta$  increases but  $1/d_i$  predominates in (41) so  $|| (D-E)^{-1} S ||$  increases. All quadrature sets have the property that  $|\mu_i|_{min}$  approaches zero as the order  $N$  of  $S_N$  is increased. Consequently, the effect of choosing a higher order  $S_N$  is to increase  $|| (D-E)^{-1} S ||$ , hence requiring a larger number of iterations to convergence. This loss of efficiency might be observed in going from  $S_2$  to  $S_4$  where the spread in  $|\mu_i|_{min}$  values is significant but is of no practical importance for higher order  $S_N$  where  $|\mu_i|_{min}$  values are quite close.

#### Convergence Properties of $S_N$ Algorithm

The following discussion applies to the  $S_N$  algorithm when  $\Delta < \frac{2|\mu_i|_{min}}{\sigma^x}$ . Then  $e_j$  and  $d_j$  are positive for all  $j$  and  $(D-E)^{-1} S$  and  $(D-E)^{-1}$  are non-negative. The sufficient condition for convergence is met for all physically realizable problems. The initial guess,  $\underline{\psi}^{(0)} = 0$ , is a convenient reference so that comparison of convergence efficiency can be made with another method later.

The  $S_N$  algorithm, under these conditions, converges in such a way that each vector component approaches its exact value in a monotone non-negative manner. This can be ascertained from applying equation (7) to the difference defined by



$$\underline{\delta}^{(\lambda+1)} = \underline{\psi}^{(\lambda+1)} - \underline{\psi}^{(\lambda)}. \quad (49)$$

Then

$$\begin{aligned} \underline{\delta}^{(\lambda+1)} &= \sum_{m=0}^{\lambda} [(D-E)^{-1}S]^m (D-E)^{-1} \underline{q} - \sum_{m=0}^{\lambda-1} [(D-E)^{-1}S]^m (D-E)^{-1} \underline{q} \\ &= [(D-E)^{-1}S]^{\lambda} (D-E)^{-1} \underline{q} \end{aligned} \quad (50)$$

which is positive for  $\underline{q} > 0$ . Consequently, some positive quantity is added to each component of  $\underline{\psi}^{(\lambda)}$  to produce the respective component of  $\underline{\psi}^{(\lambda+1)}$ .

From the definition of  $\underline{e}^{(\lambda)}$  given by (8) and  $\underline{\psi}^*$  given by (4),

$$\begin{aligned} \underline{e}^{(\lambda)} &= \underline{\psi}^* - \underline{\psi}^{(\lambda)} = \sum_{m=0}^{\infty} [(D-E)^{-1}S]^m (D-E)^{-1} \underline{q} - \sum_{m=0}^{\lambda-1} [(D-E)^{-1}S]^m (D-E)^{-1} \underline{q} \\ &= [(D-E)^{-1}S]^{\lambda} \{I + (D-E)^{-1}S + [(D-E)^{-1}S]^2 + \dots\} (D-E)^{-1} \underline{q} \end{aligned} \quad (51)$$

which is positive for  $\underline{q} > 0$ . But

$$\underline{e}^{(\lambda)} - \underline{e}^{(\lambda+1)} = \underline{\psi}^* - \underline{\psi}^{(\lambda)} - \underline{\psi}^* + \underline{\psi}^{(\lambda+1)} = \underline{\delta}^{(\lambda+1)}. \quad (52)$$

Hence

$$\underline{\delta}^{(\lambda+1)} < \underline{e}^{(\lambda)} \quad (53)$$

due to positivity of  $\underline{e}^{(\lambda)}$  and  $\underline{e}^{(\lambda+1)}$ . See Figure 2.3 for a convergence diagram.





The largest absolute error in each successive iterate is monotone decreasing. From equations (51) and (4),

$$\underline{e}^{(i)} = [(D-E)^{-1}S]^i \underline{\psi}^* . \quad (54)$$

Consequently,

$$\underline{e}^{(i+1)} = [(D-E)^{-1}S]^{i+1} \underline{\psi}^* = [(D-E)^{-1}S] \underline{e}^{(i)} . \quad (55)$$

This means that

$$e_k^{(i+1)} = \{(D-E)^{-1}S \underline{e}^{(i)}\}_k \quad \text{for all } k \text{ which}$$

does not imply that  $e_k^{(i+1)}$  is some fixed fraction of  $e_k^{(i)}$  for all  $k$  even though (52) ensures that  $e_k^{(i+1)} < e_k^{(i)}$  for all  $k$ . That is, it cannot be shown that  $e_k^{(i+1)} < \beta e_k^{(i)}$  for all  $i, k$  where  $\beta$  is a positive constant less than unity. The most that can be inferred from (55) is

$$||\underline{e}^{(i+1)}|| \leq ||(D-E)^{-1}S|| \cdot ||\underline{e}^{(i)}|| . \quad (56)$$

This means that the maximum error at each iterative step diminishes if  $|| (D-E)^{-1}S || < 1$ . This condition is met for convergence.

Similarly it can be shown from equation (50) that

$$||\underline{\delta}^{(i+1)}|| \leq ||(D-E)^{-1}S|| \cdot ||\underline{\delta}^{(i)}|| \quad (57)$$

using the same arguments and with the same consequences discussed above for the error.



It is not of much practical value to know that the error at each iterative step is less than the maximum error at the previous step. It would be of more practical value to know that the error is bounded by some fraction of the difference at each step because the differences can be calculated. Equation (51) is

$$\begin{aligned}\underline{e}^{(i)} &= [ (D-E)^{-1}S ]^i \{ I + (D-E)^{-1}S + [ (D-E)^{-1}S ]^2 + \dots \} (D-E)^{-1}q \\ &= \{ I + (D-E)^{-1}S + [ (D-E)^{-1}S ]^2 + \dots \} [ (D-E)^{-1}S ]^i (D-E)^{-1}q\end{aligned}$$

because  $[ (D-E)^{-1}S ]^i$  commutes with each term in the braces.

So

$$\underline{e}^{(i)} = \{ I + (D-E)^{-1}S + [ (D-E)^{-1}S ]^2 + \dots \} \underline{\delta}^{(i+1)}$$

due to (50). Consequently,

$$e_k^{(i)} \leq ||\underline{e}^{(i)}|| \leq \frac{||\underline{\delta}^{(i+1)}||}{1 - ||(D-E)^{-1}S||} \quad (58)$$

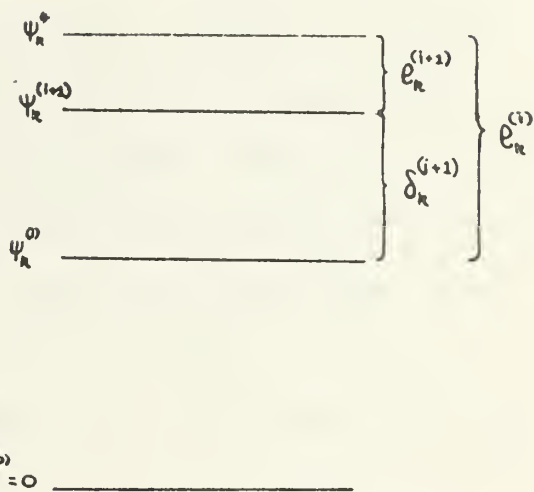
for all  $k$ . This does not provide enough information to assure that  $e_k^{(i)}$  is some fixed fraction of  $\delta_k^{(i+1)}$  for all  $k$  but it is enough to provide a practical link between the error and difference which can be exploited to derive a useful convergence criterion.



Convergence of the  $S_N$  algorithm is pictorially described in Figure 2.3 for each vector component. The iterative solution proceeds progressively towards the exact solution in a monotone positive way governed by properties (53), (56), (57), and (58).

FIGURE 2.3

$S_N$  CONVERGENCE DIAGRAM



#### Conventional Pointwise Convergence Criterion

The pointwise convergence criterion based on fractional differences,

$$\frac{\psi_k^{(i+1)} - \psi_k^{(i)}}{\psi_k^{(i)}} < \epsilon \quad (59)$$

where  $\epsilon$  is chosen arbitrarily small, is used universally in practice for shielding problems. It is especially useful in deep penetration problems where  $\underline{\psi}^*$  has elements of very small magnitude since it weights these regions more heavily. That is, iteration proceeds until the deep fluxes, which are the last to meet the convergence criterion, are converged. Its utility is based on the practical idea that, as the differences become smaller with successive iterations, the fractional amount added to each solution component is smaller than the desired accuracy after some  $i$ . Consequently,



further iteration will not add significantly to the solution.

It must be ascertained, however, whether this convergence criterion, if met, implies that the pointwise fractional error is sufficiently bounded. After all, it is desired to iterate until assured that the pointwise iteration fractional error is arbitrarily small, not just until the pointwise fractional differences are bounded.

Suppose iteration proceeds until condition (59) is met. Since

$$\underline{\delta}^{(i+1)} = \underline{e}^{(i)} - \underline{e}^{(i+1)}$$

this implies that

$$\underline{e}^{(i)} - \underline{e}^{(i+1)} < \epsilon \underline{\psi}^{(i)}$$

but  $\underline{e}^{(i+1)} = (D-E)^{-1} S \underline{e}^{(i)}$  so the above implies

$$\underline{e}^{(i)} - (D-E)^{-1} S \underline{e}^{(i)} < \epsilon \underline{\psi}^{(i)}$$

or

$$\underline{e}^{(i)} < \epsilon \underline{\psi}^{(i)} + (D-E)^{-1} S \underline{e}^{(i)} . \quad (60)$$

But by definition

$$\begin{aligned} [(D-E)^{-1} S \underline{e}^{(i)}]_k &\leq \| (D-E)^{-1} S \underline{e}^{(i)} \| \\ &\leq \| (D-E)^{-1} S \| \cdot \| \underline{e}^{(i)} \| . \end{aligned}$$





Consequently (60) implies that

$$e_k^{(i)} < \varepsilon \psi_k^{(i)} + ||(D-E)^{-1}S|| \cdot ||\underline{e}^{(i)}||$$

for all  $k$ . But from the definition

$$\underline{e}^{(i)} = \underline{\psi}^* - \underline{\psi}^{(i)}, \text{ the above inequality becomes}$$

$$e_k^{(i)} < \varepsilon [\psi_k^* - e_k^{(i)}] + ||(D-E)^{-1}S|| \cdot ||\underline{e}^{(i)}||$$

or

$$(1+\varepsilon)e_k^{(i)} < \varepsilon \psi_k^* + ||(D-E)^{-1}S|| \cdot ||\underline{e}^{(i)}||$$

for all  $k$ . But if this inequality holds for all  $k$ , it must hold for  $j$ , the value of  $k$  which corresponds to the maximum absolute value of  $e_k^{(i)}$ . Hence

$$||\underline{e}^{(i)}|| \cdot [1+\varepsilon - ||(D-E)^{-1}S||] < \varepsilon \psi_j^*$$

or

$$\frac{||\underline{e}^{(i)}||}{\psi_j^*} < \frac{\varepsilon}{1+\varepsilon - ||(D-E)^{-1}S||} \quad (61)$$

where  $j$  is the index for which  $\underline{e}^{(i)}$  attains its maximum.

Observe that (61) does not imply that the fractional error is bounded for all components of  $\underline{\psi}^*$ . However, if it is arbitrarily assumed that

$$\psi_k^* \geq \psi_j^* \quad (62)$$

for all  $k$ , expression (61) implies that



$$\frac{||e_k^{(i)}||}{\psi_k^*} < \frac{\epsilon}{1+\epsilon - ||(D-E)^{-1}S||}$$

or that

$$\frac{e_k^{(i)}}{\psi_k^*} < \frac{\epsilon}{1+\epsilon - ||(D-E)^{-1}S||} \quad (63)$$

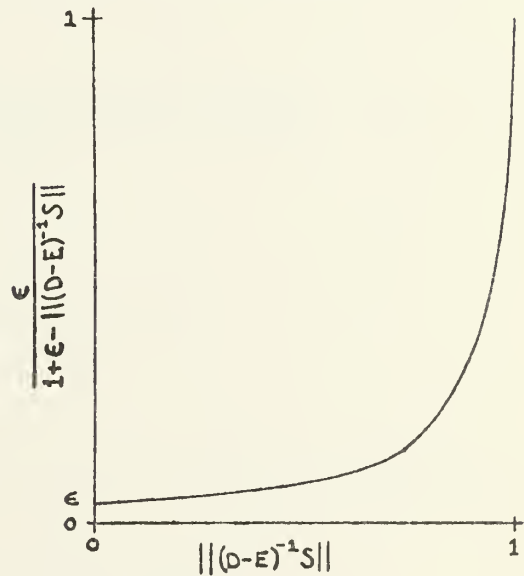
for all  $k$ . But even under the dubious assumption (62), this does not imply a satisfactory bound on the fractional error. Figure 2.4 displays a plot of the bound versus  $||(D-E)^{-1}S||$ .

Observe that, as  $||(D-E)^{-1}S||$  approaches unity, the bound grows to 1. That is, up to

100 percent fractional error is implied by invoking (59) as a convergence criterion. This criterion is useful and practical for  $||(D-E)^{-1}S|| < 0.9$  but for larger values it is a poor choice because the resulting bound on the fractional error is too large.

FIGURE 2.4

BOUND ON FRACTIONAL ERROR



#### An Improved Pointwise Convergence Criterion

Implicit in the concept of a practical convergence criterion is that iteration is terminated only after the fractional error is arbitrarily small. Since the exact solution is not known, it is necessary to iterate on fractional differences, which are known.  $||(D-E)^{-1}S||$  can be calculated for the stated  $S_N$  problem so it is possible



to establish a convergence criterion based on fractional differences which implies that the fractional errors are arbitrarily small.

Suppose iteration proceeds until

$$\frac{||\underline{\delta}^{(i+1)}||}{\psi_k^{(i)}} < \frac{\epsilon}{1-\epsilon} [1 - ||(D-E)^{-1}S||] \quad (64)$$

for all  $k$  where  $\epsilon$  is some arbitrarily small positive number.

This implies that

$$\frac{||\underline{\delta}^{(i+1)}||}{1 - ||(D-E)^{-1}S||} < \frac{\epsilon \psi_k^{(i)}}{1-\epsilon} \text{ for all } k.$$

But repeating (58)

$$e_k^{(i)} \leq \frac{||\underline{\delta}^{(i+1)}||}{1 - ||(D-E)^{-1}S||} \text{ so the above}$$

inequality implies that

$$e_k^{(i)} < \frac{\epsilon}{1-\epsilon} \psi_k^{(i)} \text{ for all } k.$$

But by definition  $\underline{\psi}^{(i)} = \underline{\psi}^* - \underline{e}^{(i)}$ , so the above inequality implies that

$$\underline{e}^{(i)} < \frac{\epsilon}{1-\epsilon} [\underline{\psi}^* - \underline{e}^{(i)}]$$

or

$$\underline{e}^{(i)} < \epsilon \underline{\psi}^*$$

or finally

$$\frac{\psi_k^* - \psi_k^{(i)}}{\psi_k^*} < \epsilon \quad (65)$$



for all  $k$ . Consequently, upon invoking convergence criterion (64), the convergence properties of the  $S_N$  algorithm assure that the fractional iteration error is arbitrarily small. This is precisely the goal for a machine convergence criterion.

For the  $S_N$  problem discussed here, equation (41) allows the exact computation of  $|| (D-E)^{-1} S ||$  and  $\epsilon$  is arbitrarily chosen. Of course for problems in which  $|| (D-E)^{-1} S ||$  is not obtainable, it is necessary to use (59) as the convergence criterion but recognition of its inability to guarantee a satisfactory bound on the fractional error for problems involving strongly scattering media is imperative.

FIGURE 2.5

Figure 2.5 reveals that **BEHAVIOR OF IMPROVED CONVERGENCE CRITERION**

the convergence constant,

$$\frac{\epsilon}{1-\epsilon} [1 - || (D-E)^{-1} S ||]$$

vanishingly small as

$|| (D-E)^{-1} S ||$  approaches unity.

For predominantly scattering

media  $|| (D-E)^{-1} S ||$  is quite close to unity. It is necessary to use the improved convergence criterion (64) for

these problems. For weakly scattering media, i.e.  $\sigma^s / \sigma^t <$

0.9, the conventional convergence criterion is acceptable.

Table II shows that the effect of using the new convergence criterion is small for  $|| (D-E)^{-1} S || < 0.9$  but overpowering for  $|| (D-E)^{-1} S || > 0.9$ .

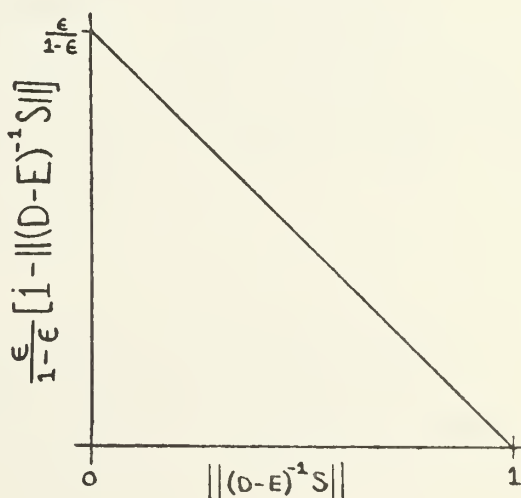






TABLE II  
IMPROVED CONVERGENCE CRITERION  
FOR  $\epsilon = 10^{-4}$

$   (D-E)^{-1} S   $	$\frac{\epsilon}{1-\epsilon} \left[ 1 -    (D-E)^{-1} S    \right]$
0.5	$0.5 \times 10^{-4}$
0.9	$10^{-5}$
0.99	$10^{-6}$
0.999	$10^{-7}$

The improved convergence criterion imposes a much more severe condition for convergence than does the conventional convergence criterion, especially for predominantly scattering media. For these problems, convergence is slow even using the conventional criterion. Imposing the improved convergence criterion makes a bad situation worse. It is necessary, however, if assurance is required that the fractional error is arbitrarily small.

#### Computer Experiment

A sample  $S_N$  problem, described by equations (18), was run on a 360/67 IBM computer with the following parameters:

- Slab width = 10.0 cm
- $R = 30$  spatial intervals
- $\sigma^t = 1.0 \text{ cm}^{-1}$
- $\sigma^s = \text{varied}$
- $\epsilon = 10^{-4}$



$N = 6$  ordinates using Gauss quadrature set<sup>61</sup>

Uniform source,  $q_j(x) = 1.0$  for all  $j$ .

It is worthy of note that any of the more recently derived mechanical quadrature sets,<sup>23,62</sup> could have been used but the Gauss set is satisfactory to demonstrate convergence properties of the  $S_N$  algorithm. This set will be used throughout.

A copy of the computer program and samples of the computer output are listed in Appendix A. Table III lists the results. The number of iterations to convergence are tabulated for various  $\sigma^s/\sigma^t$  ratios using each of three different convergence criterion.

Observe that, regardless of the convergence criterion used, problems involving predominantly absorbing media required fewer iterations to converge than did those for scattering media. The number of iterations to convergence is a monotone increasing function of  $\sigma^s/\sigma^t$ .

Comparing columns two and three shows the effect of converging on the maximum difference instead of the pointwise difference. As expected, the maximum difference criterion is more severe since it takes more iterations to meet it than the pointwise difference criterion for each value of  $\sigma^s/\sigma^t$ . This is expected because

$$\frac{||\delta_k^{(i+1)}||}{\psi_k^{(i)}} > \frac{\delta_k^{(i+1)}}{\psi_k^{(i)}} \quad \text{for all } k \text{ by definition.}$$



TABLE III

NUMBER OF ITERATIONS TO CONVERGENCE  
 $\epsilon = 10^{-4}$

$\frac{\sigma^{\delta}}{\sigma^t}, \text{ cm}^{-1}$	Convergence Criterion			% Increase of Column 4 Over Column 2
	$\frac{\delta_k^{(\lambda+1)}}{\psi_k^{(\lambda)}} < \epsilon$	$\frac{\delta_k^{(\lambda+1)}}{\psi_k^{(\lambda)}} < \epsilon$	$\frac{\delta_k^{(\lambda+1)}}{\psi_k^{(\lambda)}} < \frac{\epsilon}{1-\epsilon} [1 -   (D-E)^{-1}S  ]$	
0.5	14	16	17	21.4
0.9	57	73	91	59.6
0.99	171	242	374	118
0.999	219	317	586	167
0.9999	225	327	699	211

For this particular problem,  $||(D-E)^{-1}S|| = \frac{\sigma^{\delta}}{\sigma^t}$ .



Comparison of columns two and four shows the effect of the improved convergence criterion which guarantees that the fractional iteration error is less than  $\epsilon$ . Its effect includes the effect discussed in the preceding paragraph and has the additional effect of  $|| (D-E)^{-1} S ||$ . Both effects increase the number of iterations to convergence. The effect of  $|| (D-E)^{-1} S ||$  becomes more dominant as  $\sigma^{\delta} / \sigma^t$  increases above 0.9. This is due to the direct linear relation  $\sigma^{\delta}$  has on  $|| (D-E)^{-1} S ||$ .

A comparison of solutions, one of which met convergence criterion (59), the other meeting the improved convergence criterion (64), was made for the values of  $\sigma^{\delta} / \sigma^t$  listed in Table IV.

TABLE IV  
COMPARISON OF SOLUTION VALUES  
 $\epsilon = 10^{-4}$

$\sigma^{\delta} / \sigma^t$	Agreement of Conventional Convergence Criterion Solution with Improved Convergence Criterion Solution
0.5	Agreement in 4th significant figure
0.9	All agree to 2nd significant figure, many to 3rd
0.99	All agree to 2nd significant figure, some to 3rd
0.999	All agree to 2nd significant figure, some to 3rd
0.9999	All agree to 2nd significant figure, few to 3rd

For this problem  $|| (D-E)^{-1} S || = \sigma^{\delta} / \sigma^t$ .





The above table reveals that agreement exists only to the second significant figure for  $\sigma^s/\sigma^t > 0.9$ . From previous discussion it was established that a more accurate solution results when a larger number of iterations are made. Consequently the improved convergence criterion solution must be closer to the exact solution than the conventional convergence criterion solution because more iterations were performed for the former. The above table shows that the conventional convergence criterion solution agreed to only the second significant figure with the more accurate improved convergence criterion solution. This illustrates that the expected accuracy of  $\epsilon = 10^{-4}$  was not achieved for large values of  $\sigma^s/\sigma^t$  using the conventional convergence criterion.

Tables III and IV provide vivid illustrations of the necessity for using the improved convergence criterion for problems with  $||(\mathbf{D}-\mathbf{E})^{-1}\mathbf{S}|| > 0.9$  if an arbitrarily small fractional iterative error is required.

The overall effect of using the improved convergence criterion is insignificant for problems involving strongly absorbing media for which  $||(\mathbf{D}-\mathbf{E})^{-1}\mathbf{S}||$  is small. The effect is marked, however, for predominantly scattering systems and results in additional computational work required to assure arbitrarily small fractional iterative errors. Consequently any scheme which accelerates convergence of the  $S_N$  algorithm by decreasing  $||(\mathbf{D}-\mathbf{E})^{-1}\mathbf{S}||$  would be eminently useful when invoking the new convergence criterion, especially for strong scattering media problems.



## CHAPTER III

### ACCELERATION OF $S_N$ CONVERGENCE BY SPATIAL TRANSFORMS

#### General Discussion

The previous chapter discussed how the  $S_N$  algorithm converges more rapidly for absorbing than for scattering media. As  $\sigma^a$  decreases, holding  $\sigma^t$  constant, the number of iterations to convergence decreases regardless of the choice of convergence criterion. Based on this physical argument, it is expected that a mathematical device which adds absorption to the problem will accelerate convergence. From a mathematical point of view, an operation on the  $S_N$  equations which decreases the norm of the iteration matrix will improve the efficiency of the algorithm. A new method is presented here which incorporates both ideas.

#### General Spatial Transform

A transform of the type

$$\psi(x) = \phi(x) f^\alpha(x) \quad (1)$$

has been used to provide an effective importance sampling device in the solution of the transport equation by Monte Carlo methods.<sup>63</sup> It biases the sampling distribution towards more important directions, thereby reducing the variance in Monte Carlo methods. This leads to improved statistical accuracy for a given calculational effort.



Transforms of this type have been used by the author to accelerate convergence of the  $S_N$  algorithm for certain problems. Transforms which have proven successful are:

$$\psi_j(x) = \phi_j(x) e^{\alpha x}, \quad (2)$$

$$\psi_j(x) = \phi_j(x) \tanh^{\alpha} \left( \frac{x+b}{w} \right), \quad (3)$$

and

$$\psi_j(x) = \phi_j(x) \left[ \frac{x+b}{\ln(x+b)} \right]^{\alpha} \quad (4)$$

where  $\alpha$  is an arbitrarily chosen acceleration parameter.  $w$  and  $b$  are parameters chosen to restrict the range of the arguments. These transforms are applied to the angular discretized transport equations. The most effective transform of those listed is (2).

#### The Half-Range Problem

The spatial transform accelerates convergence of the  $S_N$  algorithm for the deep penetration infinite slab problem under the following assumptions:

- i) steady state
- ii) homogeneous medium
- iii) angular flux has no azimuthal dependence
- iv) high energy particles are scattered only in forward directions
- v) forward scattering is equally distributed in direction.

A consequence of these assumptions is that the transport equation has the form



$$\mu \frac{\partial \psi(x, \mu)}{\partial x} + \sigma^t \psi(x, \mu) = \int_0^1 \sigma^s f(\mu' \rightarrow \mu) \psi(x, \mu') d\mu' + q(x, \mu) \quad (5)$$

valid for

$$0 < \mu \leq 1 .$$

The anisotropic forward scattering assumption is valid for high energy neutrons and gammas. The assumption that the forward scattered particles are equally distributed in angle is a simplification of the usual Legendre Polynomial approximation and is made strictly for convenience. The more accurate description of the forward scattering anisotropy could be treated by the method.

The scattering distribution function, under assumption v) is normalized by recognizing that  $f(\mu' \rightarrow \mu) = \text{const}$  and

$$\int_0^1 (\text{const}) d\mu = 1 . \quad (6)$$

This simply states that the probability that a scattered neutron emerge into some allowed direction is unity. A consequence of this normalization is that

$$f(\mu' \rightarrow \mu) = 1 . \quad (7)$$

Angular approximation is accomplished by discretizing equation (5) in the  $N/2$  forward directions of the previously described quadrature set. This gives the  $S_N$  approximation

$$\mu_j \frac{d\psi_j(x)}{dx} + \sigma^t \psi_j(x) = \sigma^s \sum_{n=1}^{N/2} \omega_n \psi_n(x) + q_j(x) \quad (8)$$





with  $j = 1, 2, \dots, N/2$ . Quadrature weights obey

$$\sum_{n=1}^{N/2} \omega_n = 1 \quad (9)$$

and all  $\mu_j > 0$ . The angular quadrature set is the positive half of the one used for the full-range problem.

Spatial discretization is accomplished in the same manner described in the previous chapter to give

$$d_j \psi_{k+1,j} - e_j \psi_{k,j} = \frac{\sigma \Delta}{2} \sum_{n=1}^{N/2} \omega_n (\psi_{k+1,n} + \psi_{k,n}) + q_{k+1/2,j} \quad (10a)$$

for  $j = 1, 2, \dots, N/2$  and  $k = 1, 2, \dots, R$

where

$$d_j = \frac{2\mu_j + \Delta \sigma^t}{2\Delta} \quad (10b)$$

and

$$e_j = \frac{2\mu_j - \Delta \sigma^t}{2\Delta} \quad (10c)$$

and  $R$  is the number of equi-spaced spatial increments,  $\Delta$ .

The  $S_N$  algorithm, as before, solves this system of equations iteratively as described by

$$d_j \psi_{k+1,j}^{(i+1)} - e_j \psi_{k,j}^{(i+1)} = \frac{\sigma \Delta}{2} \sum_{n=1}^{N/2} \omega_n (\psi_{k+1,n}^{(i)} + \psi_{k,n}^{(i)}) + q_{k+1/2,j} \quad (11)$$

where  $i$  is an iteration index. This set of equations is divided by  $d_j$  to give the computer-solved  $S_N$  algorithm



$$\psi_{k+1,j}^{(i+1)} = \frac{e_j}{d_j} \psi_{k,j}^{(i+1)} + \frac{1}{d_j} \left\{ \frac{\sigma \Delta N}{2} \sum_{n=1}^{N/2} \omega_n \left( \psi_{k+1,n}^{(i)} + \psi_{k,n}^{(i)} \right) + q_{k+1/2,j} \right\}. \quad (12)$$

Numerical results for this algorithm with the first collision source

$$q_{k+1/2,j} = e^{-\left(\sigma \tau \chi_{k+1/2}\right) / \mu_j} \quad (13)$$

and vacuum boundary conditions

$$\psi_{1,j} = 0 \quad (14)$$

for all  $j$ , will be displayed and discussed later.

#### Iterative Matrix Formulation

The  $S_N$  algorithm (12), (14) with source (13) has the matrix description

$$(D-E)\underline{\psi}^{(i+1)} = S\underline{\psi}^{(i)} + \underline{q} \quad (15)$$

derived from equations (11).

If the equations are arranged so that the solution vector has the order

$$\underline{\psi} = \begin{bmatrix} \psi_{2,1} \\ \psi_{3,1} \\ \vdots \\ \psi_{R+1,1} \\ \psi_{2,2} \\ \psi_{3,2} \\ \vdots \\ \psi_{R+1,2} \\ \vdots \\ \psi_{R+1,N/2} \end{bmatrix} \quad (16)$$







$$\begin{bmatrix} d_i & & & \circ \\ -e_i & d_i & & \\ & -e_i & d_i & \\ & & \ddots & \ddots \\ \circ & & & \ddots & \ddots & -e_i & d_i \end{bmatrix} = B_i . \quad (19)$$





and

$$s_j = \frac{\sigma}{2} \omega_j. \quad (22)$$

Observe that this matrix formulation is the upper left quadrant of blocks of the full-range  $S_N$  matrix formulation and only the elements  $s_j$  are different.

Due to the block diagonal structure of  $(D-E)$ , and the bi-diagonal form of each block,  $(D-E)^{-1}$  is simply

$$\begin{bmatrix} B_1^{-1} & & & & \\ & B_2^{-1} & & & \\ & & \ddots & & \\ & & & \ddots & \\ & & & & B_{N/2}^{-1} \end{bmatrix} = (D-E)^{-1} \quad (23)$$

where



$$\begin{array}{l}
 \text{kth row} \\
 \left[ \begin{array}{ccccccc}
 \frac{1}{d_i} & & & & & & \\
 \frac{e_i}{d_i^2} & \frac{1}{d_i} & & & & & \\
 \frac{e_i^2}{d_i^3} & \frac{e_i}{d_i^2} & \frac{1}{d_i} & & & & \\
 \vdots & & & \ddots & & & \\
 \frac{e_i^{k-1}}{d_i^k} & \frac{e_i^{k-2}}{d_i^{k-1}} & \dots & \dots & \dots & & \\
 \vdots & \vdots & & & & \frac{1}{d_i} & \\
 \vdots & \vdots & & & & & \\
 \frac{e_i^{R-2}}{d_i^{R-1}} & \frac{e_i^{R-3}}{d_i^{R-2}} & \dots & \dots & \dots & \frac{e_i}{d_i^2} & \frac{1}{d_i} \\
 \frac{e_i^{R-1}}{d_i^R} & \frac{e_i^{R-2}}{d_i^{R-1}} & \dots & \dots & \dots & \frac{e_i^2}{d_i^3} & \frac{e_i}{d_i^2} & \frac{1}{d_i}
 \end{array} \right] = B_i^{-1}
 \end{array} \quad (24)$$

and  $i$  is the index for  $\mu_i$ . Each block is of dimension  $R$  by  $R$ .  $(D-E)^{-1}$  can be applied in its general form to equation (15) to produce

$$\underline{\psi}^{(i+1)} = (D-E)^{-1} S \underline{\psi}^{(i)} + (D-E)^{-1} \underline{q} \quad (25)$$

In this equation

$$(D-E)^{-1} S = \begin{array}{|c|c|c|c|}
 \hline
 B_1^{-1} S_{BD_1} & B_1^{-1} S_{BD_2} & \dots & B_1^{-1} S_{BD_{N/2}} \\
 \hline
 B_2^{-1} S_{BD_1} & B_2^{-1} S_{BD_2} & \dots & B_2^{-1} S_{BD_{N/2}} \\
 \hline
 \vdots & \vdots & & \vdots \\
 \hline
 B_{N/2}^{-1} S_{BD_1} & B_{N/2}^{-1} S_{BD_2} & \dots & B_{N/2}^{-1} S_{BD_{N/2}} \\
 \hline
 \end{array} \quad (26)$$



Observe that this matrix is the upper-left quadrant of blocks of the full-range iteration matrix of the previous chapter.

Each block has the form

$$\begin{array}{c}
 \text{the } k^{\text{th}} \text{ row} \\
 B_{ij}^{-1} S_{BD_j} = \omega_j \frac{\sigma_j^3}{2}
 \end{array}
 \begin{array}{|c|c|c|c|c|c|c|c|}
 \hline
 & \frac{1}{d_i} & & & & & & \\
 \hline
 \frac{e_i}{d_i^2} + \frac{1}{d_i} & & \frac{1}{d_i} & & & & & \\
 \hline
 \frac{e_i^2}{d_i^3} + \frac{e_i}{d_i^2} & \frac{e_i}{d_i^2} + \frac{1}{d_i} & & \frac{1}{d_i} & & & & \\
 \hline
 \vdots & \vdots & & \vdots & & & & \\
 \hline
 \frac{e_i^{k-1}}{d_i^k} + \frac{e_i^{k-2}}{d_i^{k-1}} & \frac{e_i^{k-2}}{d_i^{k-1}} + \frac{e_i^{k-3}}{d_i^{k-2}} & \frac{e_i^{k-3}}{d_i^{k-2}} + \frac{e_i^{k-4}}{d_i^{k-3}} & \dots & & & & \\
 \hline
 \vdots & \vdots & \vdots & & & & & \\
 \hline
 \frac{e_i^{R-3}}{d_i^{R-2}} + \frac{e_i^{R-4}}{d_i^{R-3}} & \frac{e_i^{R-4}}{d_i^{R-3}} + \frac{e_i^{R-5}}{d_i^{R-4}} & \frac{e_i^{R-5}}{d_i^{R-4}} + \frac{e_i^{R-6}}{d_i^{R-5}} & & \frac{1}{d_i} & & & \\
 \hline
 \frac{e_i^{R-2}}{d_i^{R-1}} + \frac{e_i^{R-3}}{d_i^{R-2}} & \frac{e_i^{R-3}}{d_i^{R-2}} + \frac{e_i^{R-4}}{d_i^{R-3}} & \frac{e_i^{R-4}}{d_i^{R-3}} + \frac{e_i^{R-5}}{d_i^{R-4}} & \dots & \frac{e_i}{d_i^2} + \frac{1}{d_i} & \frac{1}{d_i} & & \\
 \hline
 \frac{e_i^{R-1}}{d_i^R} + \frac{e_i^{R-2}}{d_i^{R-1}} & \frac{e_i^{R-2}}{d_i^{R-1}} + \frac{e_i^{R-3}}{d_i^{R-2}} & \frac{e_i^{R-3}}{d_i^{R-2}} + \frac{e_i^{R-4}}{d_i^{R-3}} & \dots & \frac{e_i^2}{d_i^3} + \frac{e_i}{d_i^2} & \frac{e_i}{d_i^2} + \frac{1}{d_i} & \frac{1}{d_i} & \\
 \hline
 \end{array}
 \quad (27)$$

### Calculation of the Norm

The infinity-norm of  $(D-E)^{-1}S$ , as previously defined, is easily calculated. The block row sum is

$$\begin{aligned}
 B_i^{-1} S_{BD_1} + B_i^{-1} S_{BD_2} + \dots + B_i^{-1} S_{BD_{N/2}} &= \frac{\sigma_i^3}{2} (\omega_1 + \omega_2 + \dots + \omega_{N/2}) (B_i^{-1} S_{BD}) \\
 &= \frac{\sigma_i^3}{2} B_i^{-1} S_{BD}
 \end{aligned}
 \quad (28)$$

due to (9). Here  $S_{BD}$  has the form of (21) but with unity in each non-zero matrix element. Actually (28) is  $\frac{\sigma_i^3}{2}$  times



the matrix part of equation (27). Consequently

$$|| (D-E)^{-1} S || = \frac{\sigma^\delta}{2} \left[ \frac{|e_i|}{d_i^R} + 2 \left( \frac{1}{d_i} + \frac{|e_i|}{d_i^2} + \frac{|e_i|^2}{d_i^3} + \dots + \frac{|e_i|^{R-2}}{d_i^{R-1}} \right) \right] \quad (29)$$

where as before,  $i$  is an index for the minimum absolute ordinate value in the set  $\{\mu_j\}$ . If one defines a  $\beta$

$$0 \leq \frac{|e_i|}{d_i} = \beta < 1 \quad (30)$$

equation (29) becomes

$$|| (D-E)^{-1} S || = \frac{\sigma^\delta}{2d_i} \left[ 2 \left( \frac{1-\beta^R}{1-\beta} \right) - \beta^{R-1} \right] \quad (31)$$

Sufficiency conditions for  $|| (D-E)^{-1} S || < 1$  are derived by requiring that

$$\frac{\sigma^\delta}{d_i} \frac{1}{1-\beta} < 1$$

or that

$$2(\mu_i)_{min} + \Delta\sigma^t > 2\Delta\sigma^\delta + |2(\mu_i)_{min} - \Delta\sigma^t| \quad (32)$$

This is the same inequality which gave the sufficiency conditions in Chapter II for convergence of the full-range  $S_N$  algorithm to the exact solution  $\psi^*$ . These conditions are the same for both problems and will not be restated here.





## Exponential Spatial Transform

The transform

$$\psi_j(x) = \phi_j(x) e^{\alpha x}, \quad (33)$$

where  $\alpha$  is a constant greater than zero, applied to the angularly discretized equations (8) gives

$$\mu_j \frac{d\phi_j(x)}{dx} + (\sigma^t + \alpha\mu_j)\phi_j(x) = \sigma^s \sum_{n=1}^{N/2} \omega_n \phi_n(x) + q_j(x) e^{-\alpha x} \quad (34)$$

$j = 1, 2, \dots, N/2$ . Observe that the transform has added absorption to the problem in amount  $\alpha\mu_j$  to produce a new "effective" total cross section,  $(\sigma^t + \alpha\mu_j)$  as well as changed the source.

Spatially discretizing these equations in the same way as previously described for the unmodified equations gives

$$d_j \phi_{k+1,j}^{(i+1)} - e_j \phi_{k,j}^{(i+1)} = \frac{\sigma^s}{2} \sum_{n=1}^{N/2} \omega_n (\phi_{k+1,n}^{(i)} + \phi_{k,n}^{(i)}) + q_{k+1/2,j} e^{-\alpha x_{k+1/2}} \quad (35)$$

$k = 1, 2, \dots, R$  and  $j = 1, 2, \dots, N/2$ . The algorithm in machine form is

$$\phi_{k+1,j}^{(i+1)} = \frac{e_j \phi_{k,j}^{(i+1)}}{d_j} + \frac{1}{d_j} \left\{ \frac{\sigma^s}{2} \sum_{n=1}^{N/2} \omega_n (\phi_{k+1,n}^{(i)} + \phi_{k,n}^{(i)}) + q_{k+1/2,j} e^{-\alpha x_{k+1/2}} \right\} \quad (36)$$

where

$$d_j = d_j + \frac{\alpha\mu_j}{2} = \frac{2\mu_j + \Delta\sigma^t + \Delta\alpha\mu_j}{2\Delta} \quad (37a)$$

and



$$e_j = e_j - \frac{\alpha \mu_j}{2} = \frac{2\mu_j - \Delta \sigma^t - \Delta \alpha \mu_j}{2\Delta} \quad (37b)$$

### Matrix Formulation

The  $\phi$ -domain algorithm has precisely the same matrix form as the unmodified  $S_N$  equations. That is, equations (11) through (27) describe the  $\phi$ -domain algorithm if  $e_j$  and  $d_j$  are replaced by  $e_j$  and  $d_j$  and if source and solution vectors are changed accordingly.

The infinity norm of the transform domain iteration matrix is

$$||(\mathcal{D}-E)^{-1}S|| = \frac{\sigma^s}{2} \left[ \frac{|e_i|^{R-1}}{d_i^R} + 2 \left( \frac{1}{d_i} + \frac{|e_i|}{d_i^2} + \frac{|e_i|^2}{d_i^3} + \dots + \frac{|e_i|^{R-2}}{d_i^{R-1}} \right) \right] \quad (38)$$

where  $i$  is the same index as before. Defining

$$0 \leq \frac{|e_i|}{d_i} = \gamma < 1 \quad (39)$$

The above equation becomes

$$||(\mathcal{D}-E)^{-1}S|| = \frac{\sigma^s}{2d_i} \left[ 2 \left( \frac{1-\gamma^R}{1-\gamma} \right) - \gamma^{R-1} \right] \quad (40)$$

Properties of  $||(\mathcal{D}-E)^{-1}S||$

The infinity norm of the transform domain iteration matrix is a monotone decreasing function of the acceleration parameter,  $\alpha$ . For small  $\alpha$ , the slope of  $||(\mathcal{D}-E)^{-1}S||$  with respect to  $\alpha$  is steep but decreases to near zero at  $\alpha = \alpha^*$  where



$$\alpha^* = \frac{2(\mu_i)_{min} - \Delta\sigma^t}{\Delta(\mu_i)_{min}} \quad (41)$$

which is the value of  $\alpha$  when  $e_i$  is zero. The norm value at  $\alpha^*$  is

$$||(\mathcal{D}-E)^{-1}S||_{\alpha=\alpha^*} = \frac{\Delta\sigma^s}{2(\mu_i)_{min}} \quad (42)$$

From this point the norm slowly approaches zero as  $\alpha$  approaches  $\infty$ . This behavior of  $||(\mathcal{D}-E)^{-1}S||$  with  $\alpha$  is verified by analysis of equation (40) in Appendix B.

Optimum Value of  $\alpha$

Appendix B reveals the behavior of  $||(\mathcal{D}-E)^{-1}S||$  for  $\alpha > \alpha^*$  to be

$$||(\mathcal{D}-E)^{-1}S|| = \frac{\Delta\sigma^s}{2(\mu_i)_{min}} \left\{ 1 - \frac{(\Delta\epsilon)^R + 2(\Delta\epsilon)^{R-1}}{(4 + \Delta\epsilon)^R} \right\} \quad (43)$$

where

$$\alpha = \alpha^* + \epsilon \quad (44)$$

and

$$0 < \epsilon < \infty \quad (45)$$

In the region where  $\Delta\epsilon < 1$ ,  $||(\mathcal{D}-E)^{-1}S||$  essentially takes its value at  $\alpha^*$ . Consequently very little norm reduction occurs in this region. This defines a practical "optimum" value for  $\alpha$ , that is,  $\alpha = \alpha^*$ . Figure 3.1 illustrates this "optimum" value for a particular problem. Observe that the



THE INFINITY NORM OF THE HALF-RANGE LAGUERRE COORDINATES UNMODIFIED ITERATION MATRIX IS COMPARED TO THAT OF THE TRANSFORM LAGRANGE ALGORITHM FOR VARIOUS VALUES OF THE ACCELERATION PARAMETER, ALPHA

THE PROBLEM PARAMETERS ARE:

SLAB WIDTH= 10.0 CM.

N= 40 SPATIAL INTERVALS.

DELTA=0.4333 CM.

SIGMA=1.00000 1/CM.

SIGMAE=0.99990 1/CM.

ANGULAR QUADRUPOLE SET=SIX POINT GAUSS.

MINIMUM ABSOLUTE NO(D)=0.23662

UNMODIFIED ALGORITHM COEFFICIENT E(1)/D(1)= 0.17754 .

UNMODIFIED ALGORITHM COEFFICIENT 1/D(1)= 0.82246 .

UNMODIFIED ALGORITHM NORM= 0.99990 .

ALPHA	E(1)/D(1)	1/D(1)	INFINITY NORM OF ITERATION MATRIX
0.20	0.15427	0.80663	0.99935
0.40	0.13306	0.79140	0.91278
0.60	0.11206	0.77673	0.87467
0.80	0.09183	0.76260	0.83962
1.00	0.07231	0.74897	0.80727
1.20	0.05349	0.73562	0.77732
1.40	0.03531	0.72312	0.74951
1.60	0.01775	0.71066	0.72363
1.80	0.00077	0.69900	0.69947
2.00	-0.01565	0.68753	0.69839
2.20	-0.03154	0.67643	0.69839
2.40	-0.04692	0.66569	0.69839
2.60	-0.06182	0.65528	0.69839
2.80	-0.07627	0.64519	0.69839
3.00	-0.09027	0.63541	0.69839
3.20	-0.10386	0.62592	0.69839
3.40	-0.11705	0.61671	0.69839
3.60	-0.12965	0.60776	0.69839
3.80	-0.14229	0.59908	0.69839
4.00	-0.15436	0.59063	0.69839
4.20	-0.16613	0.58242	0.69839
4.40	-0.17756	0.57444	0.69839
4.60	-0.18868	0.56667	0.69839
4.80	-0.19951	0.55911	0.69839
5.00	-0.21005	0.55175	0.69839

Figure 3.1 Iteration Matrix Norm Behavior with  $\alpha$ .





norm is not further reduced for values of  $\alpha > 2.00$ , at least to five significant figures. For this problem,  $\alpha^* = 1.80924$ . Hence an  $S_N$  problem of the type discussed here has a practical "optimum" acceleration parameter which can quickly be calculated from equation (41). Use of this value will result in the largest practical norm reduction with accompanying improved iteration efficiency.

#### Range of Utility of Transform Method

From the previous discussion, it is obvious that  $||(\mathcal{D}-E)^{-1}S||$  has reached a practical minimum value when  $e_i$  is zero. Consequently the transform method can significantly decrease the norm of the unmodified  $S_N$  iteration matrix only when  $(\mathcal{D}-E)^{-1}S$  is non-negative, that is, when

$$\Delta < \frac{2(\mu_i)_{min}}{\sigma^2} \quad . \quad (46)$$

Otherwise  $e_i$  is negative, which guarantees that  $e_i$  is negative for all  $\alpha \geq 0$ . In this case, the norm has already reached a value which decreases very slowly with increased  $\alpha$ .

The transform method has the greatest latitude for norm reduction, if (46) is met, when  $\Delta$  is chosen very small. Equation (41) reveals that  $\alpha^*$  is large when  $\Delta$  is chosen small. A large  $\alpha^*$  decreases the norm of  $||(\mathcal{D}-E)^{-1}S||$  more than a small  $\alpha^*$ . Table V shows this property for a specific problem.



TABLE V  
 $\alpha^*$  FOR VARIOUS  $\Delta$

R	$\Delta$	$\alpha^*$	$   (D-E)^{-1} S   $ at $\alpha^*$
30	0.333	1.81	0.69839
50	0.200	5.81	0.41903
100	0.100	15.81	0.20952

Problem parameters:  
slab width = 10.0 cm.  
 $\sigma^t = 1.0 \text{ cm}^{-1}$ .  
 $\sigma^s = 0.9999 \text{ cm}^{-1}$ .  
 $(\mu_i)_{min} = 0.23862$   
 $|| (D-E)^{-1} S || = 0.9999$ .

Table V shows that small  $\Delta$  allows large values of  $\alpha$  to be used resulting in vast reductions in  $|| (D-E)^{-1} S ||$  and improved convergence efficiency. The choice of  $\alpha$ , however is based primarily on the estimation of tolerable discretization error for a given problem. Consequently the transform method's utility depends upon factors other than those which most improve iterative efficiency. Once a  $\Delta$  is chosen, however,  $\alpha^*$  is easily determined. Its use provides practical maximum acceleration of convergence for that problem.

### Computer Experiment

The half-range problem algorithm previously described in this chapter was run on an IBM 360/67 computer with the following problem parameters:

Slab width = 10.0 cm  
 $R = 30$  spatial intervals  
 $\Delta = 0.3333 \text{ cm}$   
 $\sigma^t = 1.0 \text{ cm}^{-1}$



$$\sigma^{\delta} = 0.9999 \text{ cm}^{-1}$$

Six ordinate Gauss quadrature set

First collision source of unit strength

Fractional iterative error less than  $\epsilon = 10^{-4}$ .

The improved convergence criterion, described in Chapter II, was used. A program listing and sample output for unmodified  $S_N$  are included in Appendix C. The transform method program and sample output are included in Appendix D.

Table VI compares the number of iterations to convergence for various values of the acceleration parameter,  $\alpha$ .

TABLE VI  
TRANSFORM METHOD RESULTS

Alpha	Infinity Norm	Number of Iterations to Converge	Percent Decrease in Number of Iterations	Maximum Percent-age Difference in Unmodified to Transform Solutions
0	0.99990	59	--	0
0.2	0.95435	48	18.7	0.36
0.5	0.89332	46	22.0	1.1
1.0	0.80727	45	23.8	7.1
1.809*	0.69839	45	23.8	38.9
2.0	0.69839	45	23.8	49.4

Observe that  $\alpha = 0$  is the unmodified  $S_N$  result. The symbol \* signifies the optimum  $\alpha$ . For  $R = 30$ , the condition



$\Delta < \frac{2(\mu_i)_{min}}{\sigma^2}$  is met and the unmodified  $S_N$  iteration matrix is non-negative.

Table VI reveals that the transform method accelerates convergence of the  $S_N$  algorithm for the half-range problem. The acceleration parameter,  $\alpha$ , decreases  $e_j$  and increases  $d_j$  so that each non-zero element of the iteration matrix is decreased in value (see equations (26) and (27)). This produces a reduced norm and concomitant acceleration of convergence.

Values of  $\alpha$  greater than  $\alpha^*$  used here do not further reduce the norm or number of iterations to convergence. The dependence of convergence efficiency on the norm is not linear. Acceptable improvement of convergence efficiency is attained for values of  $\alpha$  well below  $\alpha^*$ .

#### Computational Effort

The computational effort of a machine algorithm is based upon the total number of machine operations performed. Since additions and subtractions require only an infinitesimal amount of computer time compared to multiplications and divisions, only the latter are tabulated. Table VII lists the number of operations in each component part of the unmodified  $S_N$  and transform method algorithms. Here  $n$  is equal to  $(R \cdot N/2)$ ,  $i$  is the number of iterations to convergence of the unmodified algorithm and  $j$  is the number of iterations required for transform algorithm convergence.





TABLE VII  
COMPUTATIONAL EFFORT COMPARISON

Quantity	Unmodified $S_N$ Algorithm	Transform Method Algorithm
Mesh sweep	$i \cdot (2n)$	$j \cdot (2n)$
Scattering source	$i [N/2+2]$	$j [N/2+2]$
Coefficients e, d	$9 (N/2)$	$13 (N/2)$
Transform source	0	n
Transform solution	0	n
Total	$i [2n + \frac{N}{2} + 2] + 9 (\frac{N}{2})$	$j [2n + \frac{N}{2} + 2] + 2n + 13 (\frac{N}{2})$

The transform method reduces computational work if,

$$j < i - 1 - \frac{4(3N-1)}{4R+3N+2} . \quad (47)$$

For most problems  $R \gg N$  so the transform method has utility even if only a few iterations are saved in its employment.

Isaacson<sup>53</sup> shows that Gaussian elimination requires

$$\frac{n(n^2-1)}{3} + n^2 \quad (48)$$

operations to solve a matrix system corresponding to the exact solution,  $\psi^*$ . Comparison of the  $S_N$  iterative technique shows a significant economy for large systems,  $n$  large, if  $i$  is not too large. Even so,  $i$  would have to be of the order  $n^2$  before the computational effort of the unmodified  $S_N$  algorithm reached that of Gauss elimination.



## Error in Transform Method Solution

The new convergence criterion

$$\max_j \frac{[\phi_j^{(i+1)} - \phi_j^{(i)}]}{\phi_k^{(i)}} < \frac{\varepsilon}{1-\varepsilon} [1 - ||(D-E)^{-1}S||] \quad (49)$$

which guarantees that

$$\frac{\phi_k^* - \phi_k^{(i)}}{\phi_k^*} < \varepsilon \quad (50)$$

for all  $k$ , was used in the computer algorithm. Using the transform (33), inequality (50) implies that

$$\frac{\psi_k^* e^{-\alpha X_k} - \psi_k^{(i)} e^{-\alpha X_k}}{\psi_k^* e^{-\alpha X_k}} < \varepsilon$$

or that

$$\frac{\psi_k^* - \psi_k^{(i)}}{\psi_k^*} < \varepsilon \quad (51)$$

for all  $k$ , where  $\psi^{(i)}$  is the  $\psi$ -domain transform method final solution. Consequently the convergence criterion (49) and convergence properties of the method guarantee that the transform method  $\psi$ -domain solution has fractional iteration errors less than  $\varepsilon$ . This same criterion was met for the unmodified  $S_N$  algorithm. The origin of the discrepancy in the  $\psi$ -domain solutions for transform method and unmodified



$S_N$  solutions, exhibited in column 5 of Table VI, is therefore not attributable to iteration error.

The origin of the discrepancy mentioned above is discretization error. The  $\phi$ -domain exact solution,  $\phi^*$ , has much greater variation over the slab width than does the unmodified  $S_N$  exact solution,  $\psi^*$ . Figures 3.2 and 3.3 demonstrate this for a particular direction. Since the spatial discretization of the derivative is accurate to order  $\Delta^2$  in both domains, it is a poorer approximation in the  $\phi$ -domain, where the solution has large curvature magnitude, than it is in the unmodified  $S_N$   $\psi$ -domain where the solution has a relatively small variation over the slab width. Consequently larger discretization errors occur in the transform method  $\phi$ -domain solution when large values of  $\alpha$  are used. At  $\alpha^*$ ,  $\phi^{(i)}$  varied seven orders of magnitude over the slab width whereas the unmodified  $S_N$   $\psi$ -domain solution varied by less than a factor of two. This accounts for large discretization errors in the  $\psi$ -domain transform method solution when  $\alpha$  is near  $\alpha^*$ . Table VI reveals, however, that as  $\alpha$  is decreased from  $\alpha^*$ , the discretization error diminishes so that the  $\psi$ -domain solutions for both algorithms agree to within less than 0.4% at  $\alpha = 0.2$ . For this  $\alpha$ , the  $\phi$ -domain solution varied less than a factor of five over the slab width, producing smaller discretization error than did larger  $\alpha$ . Here convergence was accelerated to 78.5% of the maximum acceleration obtained at  $\alpha^*$ . The value of  $\alpha = 0.2$  was a good practical choice for this



FIGURE 3.2

SAMPLE UNMODIFIED  $S_N \psi$ -DOMAIN SOLUTION

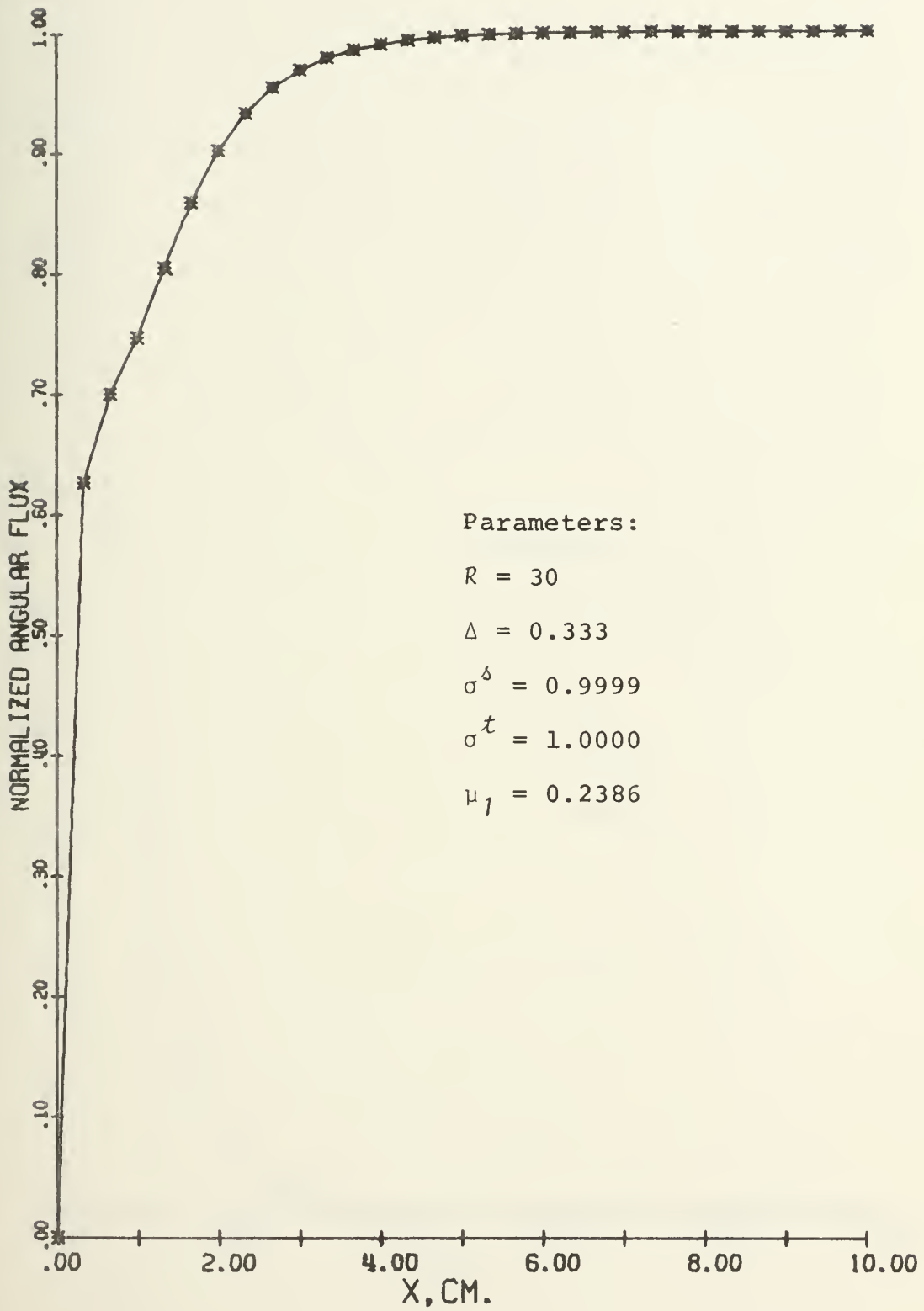
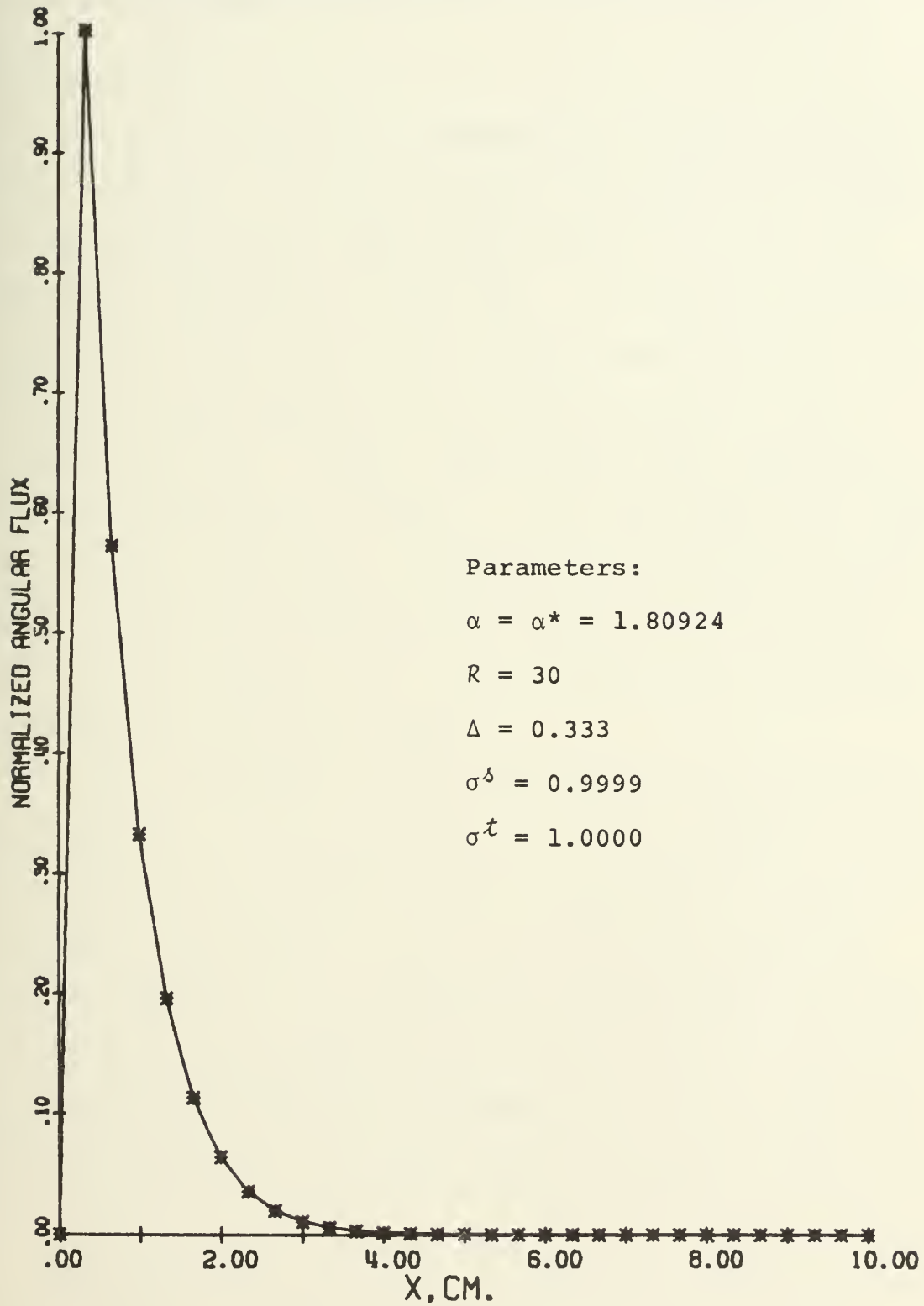






FIGURE 3.3

SAMPLE TRANSFORM METHOD  $\phi$ -DOMAIN SOLUTION





problem. For other problems, the user must make a choice of  $\alpha$  based on practical experience and a guess at the expected solution.

#### Influence of $\Delta$

Previous discussion connected with Table V revealed that, in theory, a smaller  $\Delta$  allows the choice of a larger  $\alpha^*$  with accompanying larger decrease in  $||(\mathcal{D}-E)^{-1}S||$  and number of iterations to convergence. In practice, however, such large values of  $\alpha$  are not useful because of the extremely large resulting discretization errors in the  $\phi$ -domain solution. Another consideration also limits the practical usefulness of large  $\alpha$ . For thick slabs, the transformed source, which has a factor  $e^{-\alpha x}$ , can become extremely small. Since all computers have a limit on the smallest number it can handle,  $16^{-65}$  for the IBM 360/67, it is easy to exceed this limit for large  $\alpha$ .

As a consequence of the above factors, it is best to use values of  $\alpha$  much smaller than  $\alpha^*$ , for a problem with any  $\Delta$  for which the transform method is applicable. Computer experiments conducted by this investigator have verified that the choice of  $\alpha = 0.2$  produces approximately the same acceleration of convergence and accuracy listed in Table VI for the problem described previously but with the much smaller values of  $\Delta$  resulting from  $R = 50$  and  $R = 100$ .



## Generalization of Transform Method

The transform method immediately generalizes for the half-range problem treated here to include heterogeneous slabs. In this case the cross sections are functions of position. The relatively simple expressions for  $|| (D-E)^{-1} S ||$  and  $|| (D-E)^{-1} S ||$  shown in this chapter do not occur but the matrix block form prevails and these norms can be calculated.

Transforms such as equations (3) and (4) place space dependent absorption into the problem. When using transforms of this type, care must be exercised to restrict the range of the arguments in order that finite non-negative absorption is added to the problem by the transform. Otherwise reduced or negative "effective" total cross sections will result and convergence will be decelerated in the transform domain.

It is possible that problems in  $\kappa, \mu$  and higher-dimensional geometries can be formulated in the mathematical context displayed here for the simplest geometry. If transforms can be found which place an acceleration parameter in the proper place in the iteration matrix to reduce its norm, vast savings of computational effort can be expected for these problems. The transform must be one which leaves the angular discretized  $S_N$  equations invariant. To be of practical value, such a transform must not only properly position an acceleration parameter in the iteration matrix but also must not alter the source so drastically that large



variations occur in the  $\phi$ -domain solution with the accompanying unacceptable discretization error.

Possible transform candidates are some form of the integrating factor for the angular discretized equations describing the problem after neglecting the scattering gain term. Transforms are not restricted to this class, however, and will prove useful if they meet the criterion described above.

It is doubtful that a transform can be found which is useful for all problems in a particular geometry. Experience of this investigator indicates that it is more likely that each problem in the geometry has a "best" transform which can be prescribed based upon the source, boundary conditions, and the prescriber's estimate of the form of the solution.

## Conclusions

1) The transform (33) applied to the half-range slab problem accelerates convergence of the  $S_N$  algorithm for predominantly scattering media using the improved convergence criterion.

2) The transform method is successful only for problems in which  $\Delta$  is chosen so that  $\Delta < \frac{2(\mu_i)_{min}}{\sigma^{\frac{1}{2}}}$ .

3) Significant convergence acceleration occurs for values of  $\alpha$  much smaller than  $\alpha^*$ . These smaller values of  $\alpha$  produce solutions with acceptable discretization errors.





4) A practical choice of  $\alpha$  for a particular problem must be based upon experience and the user's estimate of the expected solution characteristics.



## CHAPTER IV

### DISCRETIZATION ERROR IMPROVEMENT USING SPATIAL TRANSFORMS

Discretization error or truncation error, as it is frequently called, results from discretizing an equation in the continuous domain and comparing the discretized equation to the analytic equation. For the full-range  $S_N$  approximation of Chapter II, this process is illustrated by approximating the set of ordinary differential equations

$$\mu_j \frac{d \psi_j(x)}{dx} + \sigma^2 \psi_j(x) = \frac{\sigma^2}{2} \sum_{n=1}^N \omega_n \psi_n(x) + q_j(x) \quad (1)$$

$j = 1, 2, \dots, N$ , which are valid in the spatial continuum  $0 \leq x \leq L$ , by the spatially discretized set

$$\mu_j \left( \frac{\psi_{k+1,j} - \psi_{k,j}}{\Delta} \right) + \sigma^2 \left( \frac{\psi_{k+1,j} + \psi_{k,j}}{2} \right) = \frac{\sigma^2}{2} \sum_{n=1}^N \omega_n \left( \frac{\psi_{k+1,n} + \psi_{k,n}}{2} \right) + q_{k+1/2,j} \quad (2)$$

which uses a centered difference approximation for the derivative and a simple average for  $\psi_{k+1/2,j}$  at each midpoint  $x_{k+1/2} = \frac{x_{k+1} + x_k}{2}$ .

Expanding  $\psi_j(x_{k+1})$  and  $\psi_j(x_k)$  in Taylor series about the point  $\psi_j(x_{k+1/2})$ , truncating appropriately, and forming the proper sums produces

$$\frac{\psi_j(x_{k+1}) - \psi_j(x_k)}{\Delta} = \psi'_j(x_{k+1/2}) + \psi'''_j(x_{k+1/2}) \frac{\Delta^2}{6} + O(\Delta^2) \quad (3)$$



$$\text{where } X_k < \bar{X}_{k+1/2} < X_{k+1} \quad (4)$$

and

$$\frac{\psi_j(X_{k+1}) + \psi_j(X_k)}{2} = \psi_j(\bar{X}_{k+1/2}) + \psi''(\bar{X}_{k+1/2}) O(\Delta^2) \quad (5)$$

$$\text{where } X_k < \bar{X}_{k+1/2} < X_{k+1} . \quad (6)$$

Substituting equations (3) and (5) for the appropriately indexed quantities in equation (2) gives

$$\psi_j \left[ \frac{d\psi_j(X_{k+1/2})}{dx} + \psi_j'''(\bar{X}_{k+1/2}) O(\Delta^2) \right] + \sigma^t \left[ \psi_j(X_{k+1/2}) + \psi_j''(\bar{X}_{k+1/2}) O(\Delta^2) \right] + \frac{\sigma^s}{2} \sum_{n=1}^N \omega_n \left[ \psi_n(X_{k+1/2}) + \psi_n''(\bar{X}_{k+1/2}) O(\Delta^2) \right] = \psi_j(X_{k+1/2}) \quad (7)$$

Now evaluating  $\psi_j(x)$  at  $X_{k+1/2}$  in equations (1) and subtracting the result from equation (7) gives the discretization error

$$\tau_j(X_{k+1/2}) = O(\Delta^2) \psi_j''(\bar{X}_{k+1/2}) + \sigma^t O(\Delta^2) \psi_j''(\bar{X}_{k+1/2}) - \sigma^s O(\Delta^2) \sum_{n=1}^N \omega_n \psi_n''(\bar{X}_{k+1/2}) . \quad (8)$$

If it is assumed that the solution  $\psi_j(x)$  to equation (1) is sufficiently smooth that its third derivative exists and is bounded, that is,

$$\psi_j'''(x) \leq M \quad (9)$$

for all  $j, x$ , then

$$\tau_j(X_{k+1/2}) \leq M O(\Delta^2) + \rho O(\Delta^2) \quad (10)$$

where

$$\rho = \max_i \left[ \sigma^t \psi_i''(\bar{X}_{k+1/2}) - \sigma^s \sum_{n=1}^N \omega_n \psi_n''(\bar{X}_{k+1/2}) \right] . \quad (11)$$



The discretization error is clearly of order  $\Delta^2$  for this method. That is,  $\tau$  approaches zero as  $\Delta^2$  approaches zero.

A standard technique for diminishing the discretization error is to choose  $\Delta$  small enough, depending upon one's estimate of the variation of the solution, that the discretization error is tolerably small.

#### Transform Method

The above technique of diminishing  $\Delta$  to improve the discretization error has a practical limit. As  $\Delta$  decreases, the number of spatial mesh points increases as does the computational cost. Consequently a choice of  $\Delta$  must be based on the tradeoff between accuracy and cost.

Another method of decreasing the discretization error is suggested by (10) and (11). If a transform can be found which renders equations (1) invariant in a transform domain and diminishes the second derivative of the solution without increasing  $M$ , the discretization error will be reduced. That is, if the transform domain solution of equation (1) has less curvature magnitude over the slab than the solution  $\psi_j(x)$  of equation (1), the transform method will improve the discretization error. This method will be demonstrated in the next section for a simplified  $S_N$  problem which has an analytic solution.

#### Simplified Problem

The equation

$$\mu_0 \frac{d\psi(x)}{dx} + \sigma^t \psi(x) = \sigma^s \psi(x) + q(x) \quad (12)$$





with boundary condition

$$\psi(0) = 1.0 \quad (13)$$

and source

$$q(x) = e^{-\sigma^t x} \quad (14)$$

has a solution

$$\psi(x) = \frac{e^{-\sigma^t x}}{(\sigma^a - \mu_0 \sigma^t)} + \frac{(\sigma^a - \mu_0 \sigma^t - 1)}{(\sigma^a - \mu_0 \sigma^t)} e^{-\sigma^a x / \mu_0} \quad (15)$$

where

$$\sigma^a = \sigma^t - \sigma^s \quad (16)$$

and  $\mu_0$  is a positive real constant.

An  $S_N$ -type iterative solution of the same problem is formulated by approximating the derivative by a central difference and approximating equation (12) at a spatial midpoint as before to give

$$\psi_{k+1}^{(i+1)} = \frac{e}{d} \psi_k^{(i+1)} + \frac{1}{d} \left\{ \sigma^s \left( \frac{\psi_{k+1}^{(i)} + \psi_k^{(i)}}{2} \right) + q_{k+1/2} \right\} \quad (17)$$

with

$$\psi_1 = 1.0 \quad (18)$$

and

$$q_{k+1/2} = e^{-\sigma^t x_{k+1/2}} \quad (19)$$



Here

$$e = \frac{2\mu_0 - \Delta\sigma^t}{2\Delta} \quad (20a)$$

and

$$d = \frac{2\mu_0 + \Delta\sigma^t}{2\Delta} \quad (20b)$$

Observe that this algorithm is precisely the same form as the  $S_N$  algorithm along a  $|\mu_j|$  ray with the exception of the quadrature approximation of the scattering gain term.

### The Exponential Transform

The transform

$$\psi(x) = \phi(x) e^{-\alpha x}, \quad (21)$$

with  $\alpha > 0$ , can be applied to equation (12) to give the transform domain equation

$$\mu_0 \frac{d\phi(x)}{dx} + (\sigma^t - \alpha\mu_0)\phi(x) = \sigma^s \phi(x) + q(x) e^{\alpha x}. \quad (22)$$

Discretizing spatially, as before, gives

$$\phi_{k+1}^{(i+1)} = \frac{e}{d} \phi_k^{(i+1)} + \frac{1}{d} \left\{ \sigma^s \left( \frac{\phi_{k+1}^{(i)} + \phi_k^{(i)}}{2} \right) + q_{k+1/2} e^{\alpha x_{k+1/2}} \right\} \quad (23)$$

where

$$e = \frac{2\mu_0 - \Delta\sigma^t + \Delta\alpha\mu_0}{2\Delta} \quad (24a)$$

and

$$d = \frac{2\mu_0 + \Delta\sigma^t - \Delta\alpha\mu_0}{2\Delta}. \quad (24b)$$



Observe that this transform places the parameter  $\alpha$  into such a position that  $\frac{e}{d}$  is increased and  $\frac{1}{d}$  is increased. As shown in Chapter II, this increases the norm of the iteration matrix and decelerates convergence of the algorithm. Consequently the method is restricted to those problems for predominantly absorbing media in which the iterative efficiency is not so sensitive to the norm of the iteration matrix. For these problems, the conventional convergence criterion

$$\frac{\psi_k^{(i+1)} - \psi_k^{(i)}}{\psi_k^{(i)}} < \epsilon \quad (25)$$

can be used with negligible loss in iterative precision.

The exact  $\phi$ -domain solution of equation (22) with source

$$q(x) e^{\alpha x} = e^{-\sigma x} e^{\alpha x} = e^{x(\alpha - \sigma)} \quad (26)$$

and boundary condition

$$\phi(0) = 1.0 \quad (27)$$

is

$$\phi(x) = \frac{e^{-x(\sigma - \alpha)}}{(\sigma - \mu_0 \sigma)} + \frac{(\sigma^a - \mu_0 \sigma^t - 1)}{(\sigma^a - \mu_0 \sigma^t)} e^{-x \frac{(\sigma^a - \alpha \mu_0)}{\mu_0}} \quad (28)$$

#### Sample Problem

A problem with the parameters listed below was treated by the methods described above.



Slab width = 10.0 cm.

$R = 30$  spatial intervals.

$$\sigma^t = 1.0 \text{ cm}^{-1}.$$

$$\sigma^s = 0.2 \text{ cm}^{-1}.$$

$$\mu_0 = 0.9.$$

$$\epsilon = 10^{-4}.$$

The exact solution of equation (12) for these parameters is shown in Figure 4.1 and is

$$\psi(x) = 11e^{-.9x} - 10e^{-x}. \quad (29)$$

The exact  $\phi$ -domain solutions for various values of  $\alpha$  are shown in Figures 4.2 through 4.6. For values of  $\alpha = 0.5$  through 0.9, the exact  $\phi$ -domain solution has much less curvature magnitude over the slab width than does the exact  $\psi$ -domain solution. Consequently it is expected that the transform domain iterative algorithm (23) solution will possess smaller local discretization errors than the unmodified  $S_N$  algorithm (17).

Algorithms (17) and (23) were run on an IBM 360/67 computer to verify the expected discretization error improvement using the transform method. Table VIII summarizes the results.

The fractional errors were calculated from

$$\frac{|\psi_k^{exact} - \psi_k^{(i)}|}{\psi_k^{exact}} \quad (30)$$





FIGURE 4.1

EXACT SOLUTION FOR UNMODIFIED  $S_N$

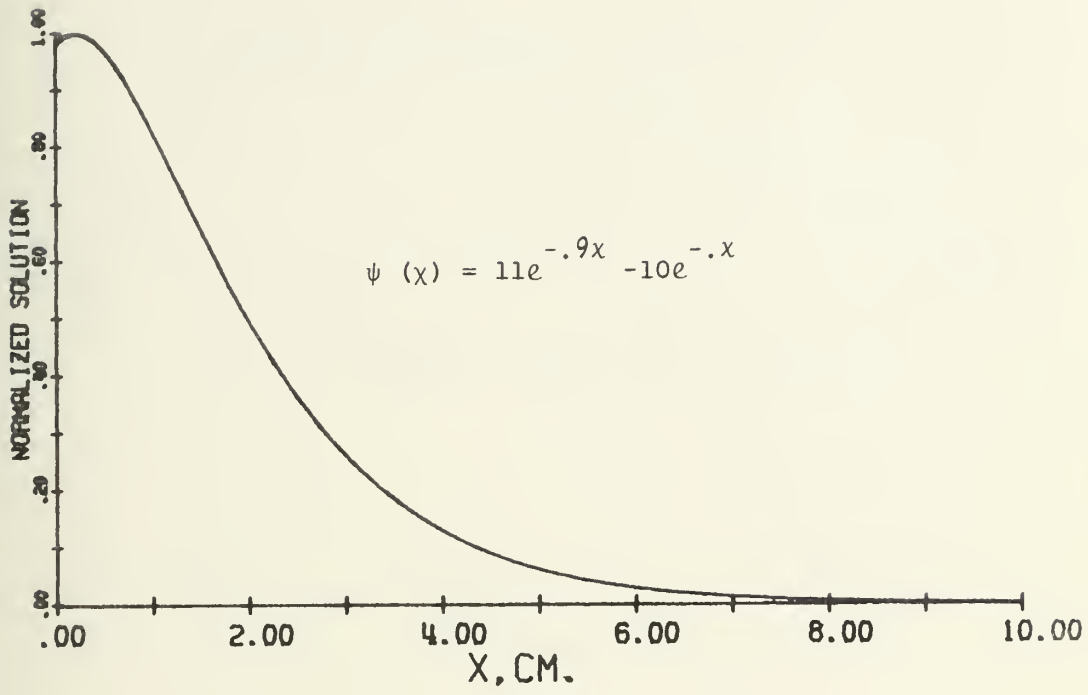


FIGURE 4.2

EXACT SOLUTION FOR  $\alpha = 0.5$

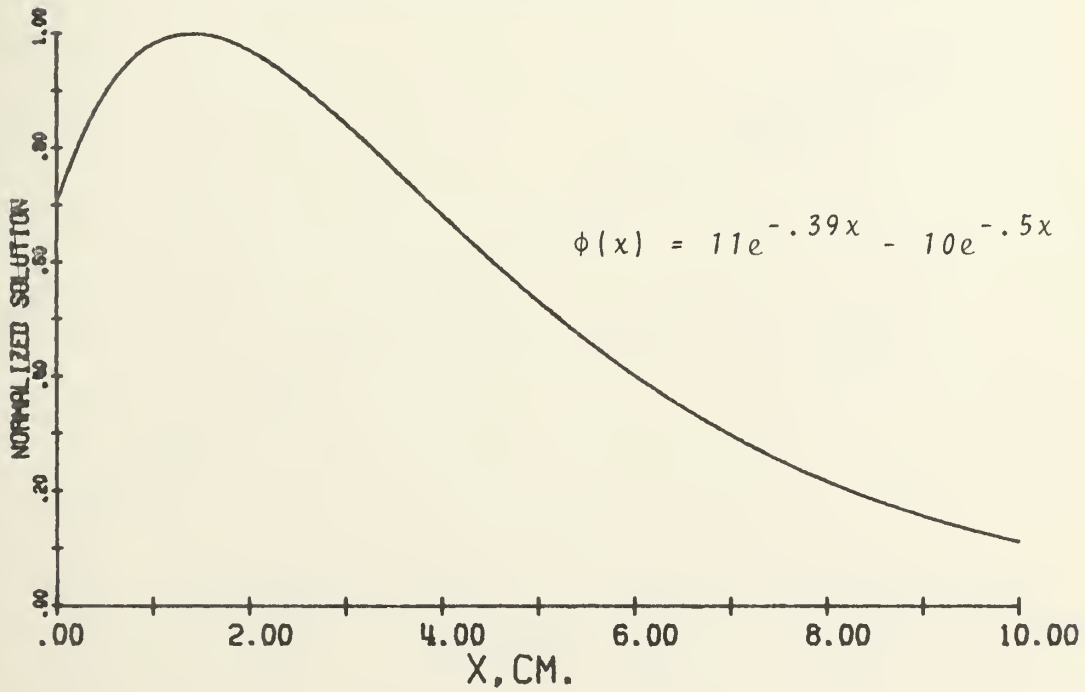




FIGURE 4.3

EXACT SOLUTION FOR  $\alpha = 0.7$ .

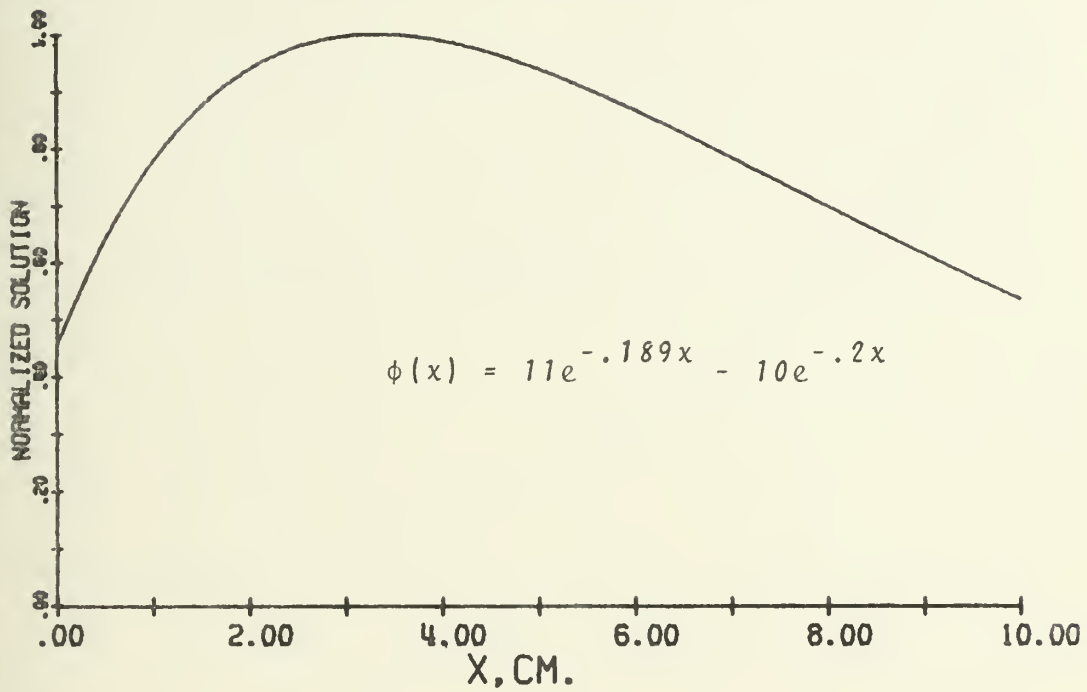


FIGURE 4.4

EXACT SOLUTION FOR  $\alpha = 0.9$

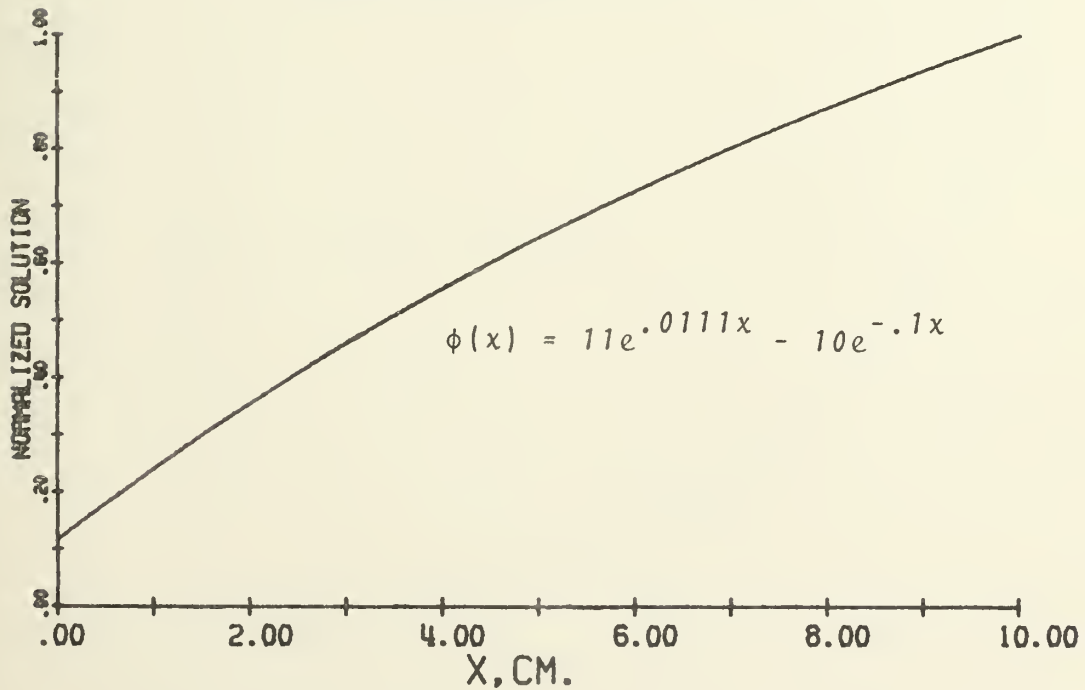




FIGURE 4.5

EXACT SOLUTION FOR  $\alpha = 1.1$

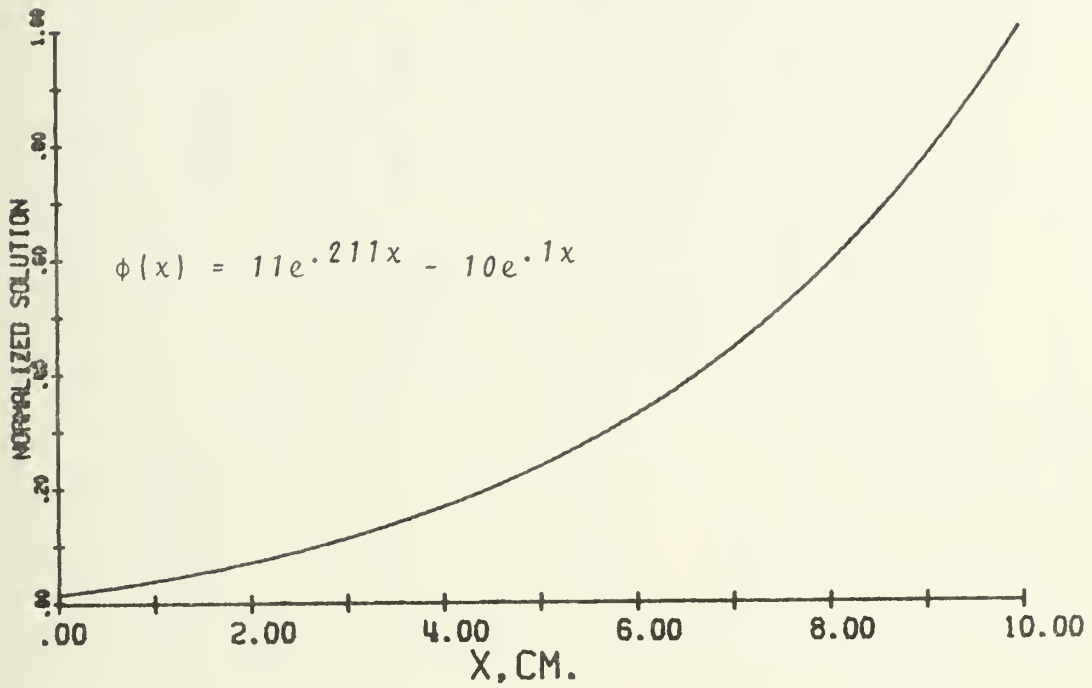


FIGURE 4.6

EXACT SOLUTION FOR  $\alpha = 1.3$

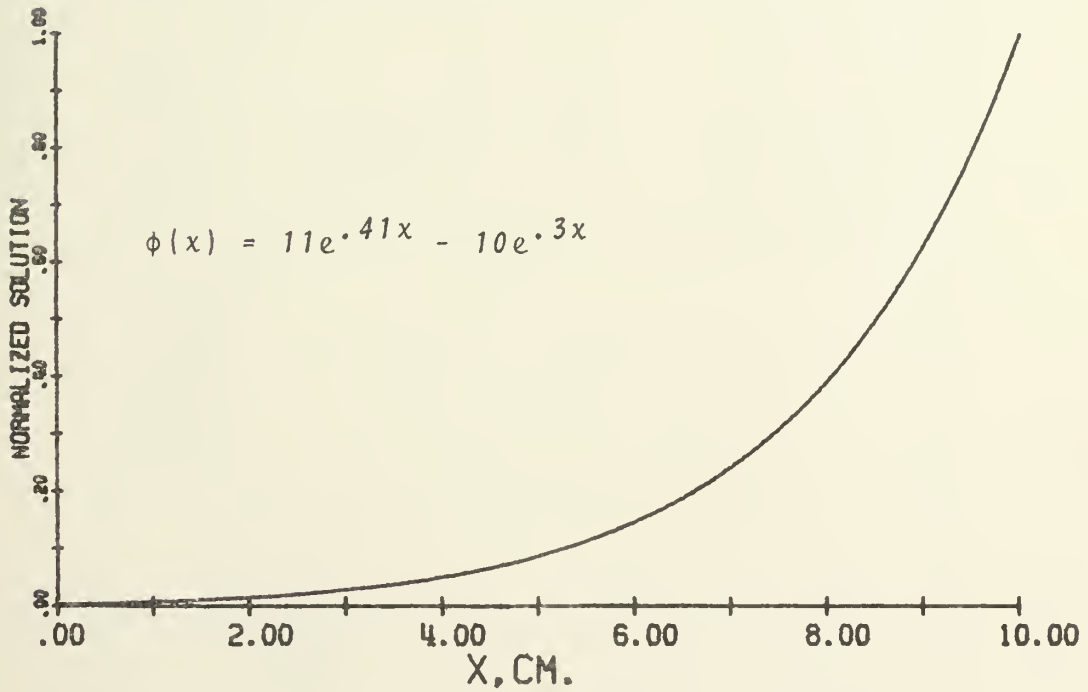




TABLE VIII

## DISCRETIZATION ERROR IMPROVEMENT

Alpha	Number of Iterations to Converge	Fractional Error Near $x = 0$	Fractional Error Near $x = 5$	Fractional Error Near $x = 10$	Remarks
Unmodified $S_N$	11	.0011	.01173	.0306	Largest errors are at large- $x$ .
0.5	11	.00056	.0000659	.00173	Vast error improvement for all $x$ .
0.7	11	.000149	.000158	.0000259	Vast error improvement for all $x$ .
0.9	11	.0000231	.0000449	.0000541	This value of $\alpha$ provided the best overall error improve- ment. Factors of 50/200/ 600 over unmodified $S_N$ .
1.1	11	.00028	.00073	.00104	Errors here still better than for unmodified $S_N$ .
1.3	11	.0129	.0039	.00616	Some small- $x$ errors larger than unmodified $S_N$ errors.





for the unmodified  $S_N$  algorithm and

$$\frac{|\phi_k^{exact} - \phi_k^{(i)}|}{\phi_k^{exact}} \quad (31)$$

for the transform domain algorithm. The errors compared, however, are for values of the unmodified  $S_N$   $\psi$ -domain solution and the transform method  $\psi$ -domain solution. These fractional errors are attributed primarily to discretization error because the unit roundoff error for the double precision mode of the computer is  $10^{-14}$  and the iterative error should be less than  $10^{-3}$  due to the convergence criterion (25) used. Certainly fractional errors greater than  $10^{-3}$ , as most unmodified  $S_N$  errors are, can be attributed to discretization error.

#### Discussion of Results

The transform method produced steady discretization error improvement with  $\alpha$  for all space points up to  $\alpha = 0.9$ . This error improvement is due to the general decrease in curvature magnitude of the exact  $\phi$ -domain solution compared to the exact  $\psi$ -domain solution over the slab width. The transform method can be used to diminish  $\rho$  in equation (11), thereby reducing the discretization error.

The value  $\alpha = 1.1$  produced error improvement over the unmodified  $S_N$  solution but less improvement than did  $\alpha = 0.9$ . Values of  $\alpha > 1.1$  produced larger discretization errors than did unmodified  $S_N$  in some regions of the slab. Observe that



the solution  $\phi(x)$ , Figure 4.4, has the least curvature magnitude at  $\alpha = 0.9$ . Also at  $\alpha > \sigma^a/\mu_0 \simeq 0.9$ , equation (28) reveals that  $\phi(x)$  has a growing exponential in the second term which dominates the solution. This suggests that predicting an optimum value for  $\alpha$  requires knowledge of the exact solution. Obviously this is not possible in more complicated practical problems but some guidance is available from the simplified problem.

#### Strategy for Determining Optimum $\alpha$

A practical value for  $\alpha$  may be obtained from the following argument. The method is only useful for predominantly absorbing media. These problems are characterized by solutions which "follow the source." That is, if the source distribution is a decaying exponential, the exact solution will have the form of a decaying exponential. Consequently a transform which changes the source to nearly a constant in the  $\phi$ -domain would probably produce a more slowly varying  $\phi$ -domain solution with accompanying smaller discretization error. For the problem treated here, that would be

$$q(x)e^{\alpha x} = e^{x(\alpha - \sigma^t)} = \text{const},$$

when

$$\alpha = \sigma^t = 1.0 .$$

This is very close to the value  $\sigma^a/\mu_0$  which was found nearly optimum by knowledge of the exact solution. In the absence



of knowledge of  $\phi(x)$ , the above strategy based on source shape could be useful. Of course if partial insight into the expected solution is available from analytic solutions to similar problems or if the user's intuition is sharp, a value of  $\alpha$  based on such considerations could prove fruitful.

#### Application to $S_N$

The  $S_N$  algorithm for the full-range slab problem, derived in Chapter II, is repeated here

$$\psi_{k+1,j}^{(i+1)} = \frac{e_j}{d_j} \psi_{k,j}^{(i+1)} + \frac{1}{d_j} \left\{ \frac{\sigma^s}{2} \sum_{n=1}^N \omega_n \psi_{k+1/2,n}^{(i)} + q_{k+1/2,j} \right\} \quad (32a)$$

for  $\mu_j > 0$  and

$$\psi_{k,j}^{(i+1)} = \frac{e_j}{d_j} \psi_{k+1,j}^{(i+1)} + \frac{1}{d_j} \left\{ \frac{\sigma^s}{2} \sum_{n=1}^N \omega_n \psi_{k+1/2,n}^{(i)} + q_{k+1/2,j} \right\} \quad (32b)$$

for  $\mu_j < 0$

where

$$e_j = \frac{2 |\mu_j| - \Delta \sigma^t}{2 \Delta} \quad (32c)$$

and

$$d_j = \frac{2 |\mu_j| + \Delta \sigma^t}{2 \Delta} \quad (32d)$$

The transform

$$\psi_j(x) = \phi_j(x) e^{-\alpha x} \quad (21)$$

with  $\alpha > 0$  applied to equation (1) gives



$$\mu_j \frac{d\phi_j(x)}{dx} + (\sigma^t - \alpha\mu_j)\phi_j(x) = \frac{\sigma^s}{2} \sum_{n=1}^N \omega_n \phi_n(x) + q_j(x)e^{\alpha x} \quad (33a)$$

for  $\mu_j > 0$  and

$$-|\mu_j| \frac{d\phi_j(x)}{dx} + (\sigma^t + \alpha|\mu_j|)\phi_j(x) = \frac{\sigma^s}{2} \sum_{n=1}^N \omega_n \phi_n(x) + q_j(x)e^{\alpha x} \quad (33b)$$

for  $\mu_j < 0$ . Observe that the transform adds absorption to the  $\mu_j < 0$  equations but diminishes absorption in the  $\mu_j > 0$  equations.

Spatial discretization is conducted in the manner previously described and coefficients of the fluxes are collected to give the  $S_N$  algorithm,

$$\phi_{k+1,j}^{(i+1)} = \frac{e_j}{d_j} \phi_{k,j}^{(i+1)} + \frac{1}{d_j} \left\{ \frac{\sigma^s}{2} \sum_{n=1}^N \omega_n \phi_{k+1/2,n}^{(i)} + q_{k+1/2,j} e^{\alpha x_{k+1/2}} \right\} \quad (34a)$$

for  $\mu_j > 0$  and

$$\phi_{k,j}^{(i+1)} = \frac{e_j}{d_j} \phi_{k+1,j}^{(i+1)} + \frac{1}{d_j} \left\{ \frac{\sigma^s}{2} \sum_{n=1}^N \omega_n \phi_{k+1/2,n}^{(i)} + q_{k+1/2,j} e^{\alpha x_{k+1/2}} \right\} \quad (34b)$$

for  $\mu_j < 0$  where

$$e_j = \begin{cases} e_j + \frac{\alpha|\mu_j|}{2} & \text{for } \mu_j > 0 \\ e_j - \frac{\alpha|\mu_j|}{2} & \text{for } \mu_j < 0 \end{cases} \quad (35a)$$

$$(35b)$$

and

$$d_j = \begin{cases} d_j - \frac{\alpha|\mu_j|}{2} & \text{for } \mu_j > 0 \\ d_j + \frac{\alpha|\mu_j|}{2} & \text{for } \mu_j < 0 \end{cases} \quad (36a)$$

$$(36b)$$





Observe that  $\alpha$  increases  $\frac{e_j}{d_j}$  and  $\frac{1}{d_j}$  for  $\mu_j > 0$ . Consequently the part of  $(D-E)^{-1}S$  which corresponds to the  $\mu_j > 0$  equations has  $\alpha$  positioned such that each non-zero matrix element is increased. Conversely,  $\alpha$  diminishes  $\frac{e_j}{d_j}$  and  $\frac{1}{d_j}$  for  $\mu_j < 0$ . This results in a decrease in the non-zero matrix elements of the iteration matrix corresponding to the  $\mu_j < 0$  equations. These properties destroy the simple block collapsing technique, demonstrated in Chapter II, used to calculate the norm of the transform domain iteration matrix. Some portions of the maximum row sum are diminished and some are increased by  $\alpha$ . Fortunately it will not be necessary to calculate  $|| (D-E)^{-1}S ||$  for the problem treated here since only predominantly absorbing media are considered. Consequently the norm will not change significantly with  $\alpha$  nor will the number of iterations to convergence.

#### Sample Problem

Equations (34), subject to the boundary conditions

$$\phi_{1,j} = 1.0 \quad \text{for } \mu_j > 0 \quad (37a)$$

and

$$\phi_{R+1,j} = 0 \quad \text{for } \mu_j < 0 \quad (37b)$$

and source

$$q_j(x) = 0 \quad \text{for all } j, \quad (38)$$



were solved on an IBM 360/67 computer. The pointwise convergence criterion

$$\frac{|\phi_k^{(i+1)} - \phi_k^{(i)}|}{\phi_k^{(i)}} < \epsilon \quad (39)$$

was used. The problem parameters are:

Slab width = 10.0 cm.

$R = 30$  spatial intervals

$\sigma^t = 1.0 \text{ cm}^{-1}$ .

$\sigma^s = 0.2 \text{ cm}^{-1}$ .

Quadrature set = six point Gauss-Legendre

$\alpha =$  Various values from 0.1 to 1.0.

The resulting  $\psi$ -domain solution will be compared to two unmodified  $S_N$  solutions of the same problem, described by equations (32), but with different spatial mesh sizes. One used  $R = 600$ , the other  $R = 30$ . Appendix E contains the programs and sample output.

#### Unmodified $S_N$ Results

Comparison of the unmodified  $S_N$  results for  $R = 600$  and  $R = 30$  shows that all  $R = 600$  values are either equal to or greater than (at least to five significant figures) the  $R = 30$  solution values. Since the  $R = 600$  solution has less discretization error than the  $R = 30$  solution, the above fact simplifies the analysis of the effect of the transform method on improving discretization error. If the transform method  $\psi$ -domain solution values are between the unmodified  $S_N$   $R = 30$  and  $R = 600$  values, the method has improved the



discretization error. The above criterion is used to judge the effectiveness of the transform method in improving discretization error.

### Transform Method Results

The data show that the transform method decreases the discretization error for the problem. Discretization error improvement is not pointwise uniform but, in general, transform method solution values approach the  $R = 600$  solution values as  $\alpha$  is increased. The bulk solution differences, displayed and defined in Table IX, diminish for each  $\mu_j$  component of the solution as  $\alpha$  increases. The total bulk difference also diminishes as  $\alpha$  increases. This means that some integral measure of the discretization error diminishes as  $\alpha$  increases through  $\alpha = 1.0$ . A closer look at the pointwise data, however, reveals that at  $\alpha = 1.0$  many transform method  $\psi$ -domain solution values have overshoot the unmodified  $S_N$   $R = 600$  solution values.

Table X displays a more detailed analysis of the pointwise discretization error improvement achieved by the transform method. It shows that discretization error is decreased at each point for values of  $\alpha$  up to 0.5. For  $\alpha > 0.5$ , discretization error is generally improved but some values overshoot the  $R = 600$  values. As  $\alpha$  grows larger, more values overshoot the  $R = 600$  values and the analysis loses its basis for comparison. All methods required the same number of iterations to converge; 10. Hence



TABLE IX

BULK SOLUTION DIFFERENCES FOR VARIOUS  $\alpha$ 

Alpha	MU(1)	MU(2)	MU(3)	MU(4)	MU(5)	MU(6)	Total
0*	0.10103	0.037411	0.026569	0.0040609	0.0024641	0.0019834	0.17352
0.1	0.09294	0.029666	0.019039	0.0035137	0.0021072	0.0016895	0.14896
0.3	0.078202	0.017448	0.0084172	0.0026179	0.0015301	0.0012161	0.10943
0.5	0.065267	0.0090181	0.0030947	0.0019507	0.0011095	0.00087339	0.081313
0.7	0.053990	0.0038904	0.0011895	0.0014677	0.00081394	0.00063493	0.061987
0.9	0.044222	0.0015471	0.00097341	0.0011245	0.00061195	0.00047407	0.048953
1.0	0.039854	0.0011347	0.00088316	0.0009915	0.00053619	0.00041443	0.043814

\*Signifies unmodified  $S_N$  with  $R = 30$  spatial intervals.

The bulk differences are defined by:

Bulk difference for MU(J) =  $\sum_k |( \text{Unmodified } R=600 \text{ solution} )_{k,j} - ( \text{transform method } R=30 \text{ solution} )_{k,j}|$

Total bulk difference =  $\sum_j \{ \text{bulk difference for MU(J)} \}$





TABLE X  
DISCRETIZATION ERROR IMPROVEMENT

Alpha	Significant Figure of Closest Agreement with $R = 600$ Algorithm Solution	Analysis of Differences between Unmodified $R = 600$ Solution and Transform Method $R = 30$ Solution	General Remarks (Agreement Refers to Comparison with $R = 600$ Unmodified $S_N$ Solution)
0*	2nd for $\mu > 0$ 5th for $\mu < 0$	All solution values are smaller than $R = 600$ values.	Agreement is generally only to first significant figure.
0.1	2nd for $\mu > 0$ 5th for $\mu < 0$	All values closer to $R = 600$ solution than are the unmodified $R = 30$ values.	Discretization error improved at each point. Agreement generally only to first significant figure.
0.3	3rd for $\mu > 0$ 5th for $\mu < 0$	All values closer to $R = 600$ solution than $\alpha = 0.1$ values are.	Discretization error improved at each point. Agreement generally to 2nd significant figure for $\mu > 0$ values. Agreement generally to 1st significant figure for $\mu < 0$ values.
0.5	3rd for $\mu > 0$ 5th for $\mu < 0$	All values but 1 out of 186 have closer values to $R = 600$ solution than did $\alpha = 0.3$ solution.	Discretization error improved at each point. One value overshoot $R = 600$ value. Agreement generally to 2nd significant figure for $\mu > 0$ values. Agreement generally to 1st significant figure for $\mu < 0$ values.



TABLE X--Continued

Alpha	Significant Figure of Closest Agreement with R = 600 Algorithm Solution	Analysis of Differences between Unmodified R = 600 Solution and Transform Method R = 30 Solution	General Remarks (Agreement Refers to Comparison with R = 600 Unmodified S <sub>N</sub> Solution)
0.7	3rd for $\mu > 0$ 5th for $\mu < 0$	All but 7 of 186 values have smaller differences from R = 600 values than did $\alpha = 0.5$ solution.	Discretization error generally improved. A few values slightly overshoot R = 600 solution. One value overshoot by 8%. Many values agree to 3rd significant figure for $\mu > 0$ . Agreement generally to 2nd significant figure for $\mu < 0$ .
0.9	5th for $\mu > 0$ 5th for $\mu < 0$	Most differences from R = 600 result are smaller than are those for $\alpha = 0.7$ .	Majority of points have improved discretization error. A few values overshoot R = 600 solution. One overshoot 9.5%. Many values agree to 4th and most agree to 3rd significant figure for $\mu > 0$ . Agreement generally to 3rd significant figure for $\mu < 0$ .
1.0	4th for $\mu > 0$ 5th for $\mu < 0$	Overshoot on many values causes larger differences from R = 600 values than were exhibited for $\alpha = 0.9$ results.	Many values (24 out of 186) overshoot R = 600 values. One overshoot was 10.2%. Many values agree to 4th and most agree to 3rd significant figure for $\mu > 0$ . Agreement generally to 3rd significant figure for $\mu < 0$ .



discretization error improvement was achieved at the expense of only  $R \cdot N$  extra computations.

## Conclusion

The transform method can be used to decrease the discretization error in  $S_N$  problems. This method is effective when the transform domain solution has less curvature magnitude over the slab width than the unmodified  $S_N$  solution.

The transform used for this purpose must be tailored to each individual problem. The choice of a successful transform for a specific problem is based upon intuition developed for that problem by experience, knowledge of analytic solutions to similar problems, or guess. For problems in which solutions tend to "follow the source," a transform may be devised which converts the source to a near constant in the transform domain. A possible transform candidate is some variation of the integrating factor for the transport equation neglecting the scattering gain term.



## CHAPTER V

### ROUND OFF ERROR ANALYSIS FOR ITERATIVE METHODS

#### Background

Previous chapters have discussed the concepts of iteration and discretization errors in the  $S_N$  method. Each effect was treated with regard to its role in the convergence of the algorithm to some exact solution. The approximate solution  $\underline{\psi}^{(i)}$  was shown to approach the exact solution  $\psi_j(x)$  of the angular segmented equations as  $i$  approaches  $\infty$  and  $\Delta$  approaches zero. This concept of convergence ignores the errors that occur in any machine computation due to the rounding procedure employed in floating point arithmetic. In order to be effective, however, an algorithm must remain immune to the accumulation of roundoff errors. This immunity is called numerical stability. An otherwise convergent algorithm may be driven divergent if it does not possess this property. In order to analyze the property of numerical stability, precise definitions must be made.

#### Well-Posed Computation

A numerical method, which produces a solution approximating the exact solution of the problem, is said to be a well-posed computation if the solution is insensitive





to small changes in data or to roundoff errors. Here data refers to the elements of matrices involved and the initial or boundary conditions and sources. Isaacson<sup>53</sup> defines a computing problem as an algorithm or "a set of rules specifying the order and kind of arithmetic operations (i.e. rounding rules) to be used on specified data." He also defines a computing problem to be well-posed if and only if

i) a solution exists

ii) the solution is unique, that is, when performed several times, with the same data, identical results are obtained

iii) the solution depends Lipschitz continuously on the data with a constant that is not too large. The last condition requires that "small" changes in the data must result in only "small" changes in the solution. A well-posed computation possesses the property of numerical stability. A necessary condition that a finite difference scheme be convergent is that it possess numerical stability.

#### Condition Number

Roundoff errors will in general be introduced in the course of carrying out the arithmetic required to solve the system of equations

$$A\underline{x} = \underline{b} . \quad (1)$$

But if the algorithm is well-posed, these errors can be kept within reasonable bounds. The matrix  $A$  is said to be



"well-conditioned" or "ill-conditioned" if the computation is or is not, respectively, well-posed. The condition number,  $\nu(A)$ , for  $A$  serves as a measure of ill-conditioning. The condition number is defined by

$$\nu(A) = ||A|| \cdot ||A^{-1}||. \quad (2)$$

Some important properties of the condition number are:

- i)  $\nu(A) \geq 1$  with equality only if  $A$  is orthogonal.
- ii)  $\nu(A) = \nu(A^{-1})$ .
- iii)  $\nu(\alpha A) = \nu(A)$ .

Suppose that the data  $A$  and  $\underline{f}$  of equation (1) have small perturbations or uncertainties  $\delta A$  and  $\delta \underline{f}$  respectively due to roundoff error. The computer is solving the slightly perturbed system

$$(A + \delta A)(\underline{X} + \delta \underline{X}) = \underline{f} + \delta \underline{f} \quad (3)$$

instead of system (1). Isaacson<sup>53</sup> shows that if

$$||\delta A|| < 1/||A^{-1}||, \quad (4)$$

the resulting relative uncertainty in the solution,  $\underline{X}$ , is

$$\frac{||\delta \underline{X}||}{||\underline{X}||} \leq \frac{\nu}{1-\nu \cdot \frac{||\delta A||}{||A||}} \left( \frac{||\delta \underline{f}||}{||\underline{f}||} + \frac{||\delta A||}{||A||} \right). \quad (5)$$

Observe that if  $\nu(A)$  is relatively small,  $A$  is well-conditioned and "small" relative uncertainties in the data produce "small" relative uncertainties in the solution. Conversely if  $\nu(A)$  is very large,  $A$  is ill-conditioned and



"small" relative uncertainties in the data can destroy the solution.

Forsythe<sup>64</sup> points out a popular misconception that the smallness of  $\det(A)$  causes the ill-condition of  $A$ . That is, the condition number is not a measure of how nearly  $A$  is singular, hence difficult to invert. He stresses that the size of  $v(A)$  is a far more important criterion of the "badness" of computational system (1) than either the smallness of  $\det(A)$  or the largeness of the order  $n$  of the system.

A theorem from Isaacson,<sup>53</sup> which will prove useful later, is stated here.

#### Theorem 2

If the matrix  $A$  has  $||A|| < 1$ , then  $(I \pm A)$  is non-singular and

$$\frac{1}{1+||A||} \leq ||(I \pm A)^{-1}|| \leq \frac{1}{1-||A||} . \quad (6)$$

#### Application to Iterative Methods

Isaacson,<sup>53</sup> referring to iterative methods for solving systems of equations (1), states "One of the intrinsic advantages of such methods is the fact that errors, due to roundoff or even blunders, may be damped out as the iterative procedure continues". The following analysis provides an insight into the mechanism of this intrinsic advantage.



The iterative  $S_N$  algorithm, described in Chapter II, has a matrix representation

$$(D-E)\underline{\psi}^{(\dot{i}+1)} = S\underline{\psi}^{(\dot{i})} + \underline{q} . \quad (7)$$

At each iterative step, the data  $D$ ,  $E$ ,  $S$ ,  $\underline{q}$ , and  $\underline{\psi}^{(\dot{i})}$  are known and the machine is expected to invert  $(D-E)$  exactly and multiply the result onto the right-hand-side of (7), that is, solve for

$$\underline{\psi}^{(\dot{i}+1)} = (D-E)^{-1}S\underline{\psi}^{(\dot{i})} + (D-E)^{-1}\underline{q} \quad (8)$$

precisely. The computer, however, has a limited storage capacity for each digit and must round off the input data to the last significant digit of its capacity. Consequently the uncertainty in the stationary data is  $\delta D$ ,  $\delta E$ ,  $\delta S$ , and  $\delta \underline{q}$  which are of the order of the unit roundoff error of the machine ( $10^{-14}$  for the IBM 360/67 in double precision mode). These uncertainties are propagated through the arithmetic process of inverting  $(D-E)$  and matrix multiplying the result onto appropriate right hand side vectors. Consequently even the input data  $\underline{\psi}^{(\dot{i})}$  has its uncertainty,  $\delta \underline{\psi}^{(\dot{i})}$ , carried with it in equation (7). Therefore the exact system to be solved at the  $\dot{i}+1^{st}$  iterate is not (7) but

$$(D-E)\underline{\psi}^{(\dot{i}+1)} = S\underline{\psi}_c^{(\dot{i})} + \underline{q} \quad (9)$$

where the previously computed solution,  $\underline{\psi}_c^{(\dot{i})}$ , is

$$\underline{\psi}_c^{(\dot{i})} = \underline{\psi}^{(\dot{i})} + \delta \underline{\psi}^{(\dot{i})} . \quad (10)$$





But now the machine must solve the perturbed system

$$(D+\delta D-E-\delta E) (\underline{\psi}^{(i+1)} + \underline{\delta\psi}^{(i+1)}) = (S+\delta S) (\underline{\psi}_c^{(i)} + \underline{\delta\psi}_c^{(i)}) + (\underline{q} + \delta \underline{q}) \quad (11)$$

where  $\underline{\delta\psi}_c^{(i)}$  is the roundoff error resulting from machine handling of the data  $\underline{\psi}_c^{(i)}$ . It is the same order of magnitude as  $\delta D$ ,  $\delta E$ ,  $\delta S$ , and  $\delta \underline{q}$ . These uncertainties in the input data produce an uncertainty  $\underline{\delta\psi}^{(i+1)}$  in the solution. Using equation (11), it is possible to derive an upper bound on the norm of the relative uncertainty in the solution

$$\frac{||\underline{\delta\psi}^{(i+1)}||}{||\underline{\psi}^{(i+1)}||} \quad \text{at each iterative step.}$$

#### First Iteration

Suppose the initial guess for algorithm (7) is

$$\underline{\psi}^{(0)} = 0 \quad (12)$$

with no machine error. That is, the first machine iteration is on  $\underline{q}$ . The first iterate is

$$(D-E)\underline{\psi}^{(1)} = \underline{q} \quad (13)$$

but the computer solves the perturbed system

$$(D+\delta D-E-\delta E) (\underline{\psi}^{(1)} + \underline{\delta\psi}^{(1)}) = \underline{q} + \delta \underline{q} . \quad (14)$$

Factoring out  $(D-E)$  from the left-hand-side and multiplying by  $(D-E)^{-1}$  gives

$$\left[ I + (D-E)^{-1} (\delta D - \delta E) \right] (\underline{\psi}^{(1)} + \underline{\delta\psi}^{(1)}) = (D-E)^{-1} (\underline{q} + \delta \underline{q}) . \quad (15)$$



Recognizing that

$$\underline{\psi}^{(1)} = (D-E)^{-1} \underline{q} \quad (16)$$

from (13), cancelling this equality in (15) and collecting terms in  $\underline{\delta\psi}^{(1)}$  on the left-hand-side produces

$$\left[ I + (D-E)^{-1} (\delta D - \delta E) \right] \underline{\delta\psi}^{(1)} = (D-E)^{-1} (\delta E - \delta D) \underline{\psi}^{(1)} + (D-E)^{-1} \underline{\delta q}. \quad (17)$$

Hence

$$\underline{\delta\psi}^{(1)} = \left[ I + (D-E)^{-1} (\delta D - \delta E) \right]^{-1} \left\{ (D-E)^{-1} (\delta E - \delta D) \underline{\psi}^{(1)} + (D-E)^{-1} \underline{\delta q} \right\}. \quad (18)$$

But due to Theorem 2,

$$\left\| \left[ I + (D-E)^{-1} (\delta D - \delta E) \right]^{-1} \right\| \leq \frac{1}{1 - \left\| (D-E)^{-1} (\delta D - \delta E) \right\|} \quad (19)$$

subject to the restriction that

$$\left\| \delta D - \delta E \right\| < \frac{1}{\left\| (D-E)^{-1} \right\|}. \quad (20)$$

Hence

$$\left\| \underline{\delta\psi}^{(1)} \right\| \leq \frac{1}{1 - \left\| (D-E)^{-1} (\delta D - \delta E) \right\|} \left\{ \left\| (D-E)^{-1} \right\| \cdot \left\| \delta D - \delta E \right\| \cdot \left\| \underline{\psi}^{(1)} \right\| + \left\| (D-E)^{-1} \right\| \cdot \left\| \underline{\delta q} \right\| \right\}.$$

Now divide by  $\left\| \underline{\psi}^{(1)} \right\|$  and multiply by  $\frac{\left\| (D-E) \right\|}{\left\| (D-E) \right\|}$  to obtain

$$\frac{\left\| \underline{\delta\psi}^{(1)} \right\|}{\left\| \underline{\psi}^{(1)} \right\|} \leq \frac{\nu}{1 - \left\| (D-E)^{-1} (\delta D - \delta E) \right\|} \left\{ \frac{\left\| \delta D - \delta E \right\|}{\left\| (D-E) \right\|} + \frac{\left\| \underline{\delta q} \right\|}{\left\| (D-E) \right\| \cdot \left\| \underline{\psi}^{(1)} \right\|} \right\}. \quad (21)$$

where  $\nu$  is the condition number of the matrix  $(D-E)$ , that is,



$$v = ||(D-E)|| \cdot ||(D-E)^{-1}|| \quad (22)$$

But from (13),

$$||\underline{q}|| \leq ||(D-E)|| \cdot ||\underline{\psi}^{(1)}||$$

or

$$\frac{1}{||D-E|| \cdot ||\underline{\psi}^{(1)}||} \leq \frac{1}{||\underline{q}||} \quad (23)$$

From restriction (20) and the fact that

$$||(D-E)^{-1}(\delta D - \delta E)|| \leq ||(D-E)^{-1}|| \cdot ||\delta D - \delta E|| < 1,$$

$$1 - ||(D-E)^{-1}(\delta D - \delta E)|| \geq 1 - ||(D-E)^{-1}|| \cdot ||\delta D - \delta E|| \quad \text{hence}$$

$$\frac{1}{1 - ||(D-E)^{-1}(\delta D - \delta E)||} \leq \frac{1}{1 - ||(D-E)^{-1}|| \cdot ||\delta D - \delta E||} \quad (24)$$

Using (23) and (24), inequality (21) becomes

$$\frac{||\delta \underline{\psi}^{(1)}||}{||\underline{\psi}^{(1)}||} \leq \frac{v}{1 - v \frac{||\delta D - \delta E||}{||D-E||}} \left\{ \frac{||\delta D - \delta E||}{||D-E||} + \frac{||\delta \underline{q}||}{||\underline{q}||} \right\} \quad (25)$$

Second Iteration

The second iteration treats the problem

$$(D-E)\underline{\psi}^{(2)} = S\underline{\psi}_c^{(1)} + \underline{q} \quad (26)$$

but the machine solves the perturbed system

$$(D + \delta D - E - \delta E)(\underline{\psi}^{(2)} + \delta \underline{\psi}^{(2)}) = (S + \delta S)(\underline{\psi}_c^{(1)} + \delta \underline{\psi}_c^{(1)}) + (\underline{q} + \delta \underline{q}). \quad (27)$$



Following the same procedure used during the first iteration,

$$\frac{||\underline{\psi}^{(2)}||}{||\underline{\psi}^{(2)}||} \leq \frac{\nu}{1-\nu \cdot \frac{||\delta D - \delta E||}{||D-E||}} \left\{ \frac{||\delta E - \delta D||}{||D-E||} + \frac{||\delta S||}{||D-E||} \cdot \frac{||\underline{\psi}_c^{(1)}||}{||\underline{\psi}^{(2)}||} + \frac{||S + \delta S||}{||D-E||} \cdot \frac{||\underline{\psi}_c^{(1)}||}{||\underline{\psi}^{(2)}||} + \frac{||\underline{\delta q}||}{||D-E|| \cdot ||\underline{\psi}^{(2)}||} \right\} \quad (20)$$

A bound on the quantity  $\frac{||\underline{\psi}_c^{(1)}||}{||\underline{\psi}^{(2)}||}$  can be derived from (26). That is,

$$\underline{\psi}^{(2)} = (D-E)^{-1} S \underline{\psi}_c^{(1)} + (D-E)^{-1} \underline{q}$$

or

$$\underline{\psi}_c^{(1)} = [(D-E)^{-1} S]^{-1} [\underline{\psi}^{(2)} - (D-E)^{-1} \underline{q}] .$$

Consequently

$$||\underline{\psi}_c^{(1)}|| \leq ||[(D-E)^{-1} S]^{-1}|| [||\underline{\psi}^{(2)}|| + ||(D-E)^{-1}|| \cdot ||\underline{q}||]$$

or

$$\frac{||\underline{\psi}_c^{(1)}||}{||\underline{\psi}^{(2)}||} \leq ||[(D-E)^{-1} S]^{-1}|| \left[ 1 + \frac{||\underline{(D-E)^{-1}}|| \cdot ||\underline{q}||}{||\underline{\psi}^{(2)}||} \right] \quad (29)$$

A bound on  $\frac{1}{||\underline{\psi}^{(2)}||}$  on the R.H.S. of (29) can be derived by using the unperturbed system

$$\underline{\psi}^{(2)} = (D-E)^{-1} S \underline{\psi}^{(1)} + (D-E)^{-1} \underline{q} . \quad (30)$$

From equation (13)

$$\underline{\psi}^{(1)} = (D-E)^{-1} \underline{q} \quad (31)$$





which substituted into (30) gives

$$[I + (D-E)^{-1}S]\underline{\psi}^{(1)} = \underline{\psi}^{(2)}$$

or

$$\underline{\psi}^{(1)} = [I + (D-E)^{-1}S]^{-1}\underline{\psi}^{(2)} . \quad (32)$$

Using Theorem 2,

$$||\underline{\psi}^{(1)}|| \leq \frac{||\underline{\psi}^{(2)}||}{1 - ||(D-E)^{-1}S||}$$

subject to the restriction that

$$||(D-E)^{-1}S|| < 1 . \quad (33)$$

But recall that (33) is the condition that the  $S_N$  algorithm must meet to guarantee convergence so it is met a priori.

Consequently

$$\frac{1}{||\underline{\psi}^{(2)}||} \leq \frac{1}{(1 - ||(D-E)^{-1}S||) \cdot ||\underline{\psi}^{(1)}||} . \quad \text{But from (23),}$$

$$\frac{1}{||\underline{\psi}^{(1)}||} \leq \frac{||D-E||}{||\underline{q}||} \quad \text{so the above inequality becomes}$$

$$\frac{1}{||\underline{\psi}^{(2)}||} \leq \frac{||D-E||}{||\underline{q}|| \cdot (1 - ||(D-E)^{-1}S||)} . \quad (34)$$

Using (34) on the R.H.S. of (29) produces

$$\frac{||\underline{\psi}_c^{(1)}||}{||\underline{\psi}^{(2)}||} \leq ||[(D-E)^{-1}S]^{-1}|| \left[ \frac{1 + v - ||(D-E)^{-1}S||}{1 - ||(D-E)^{-1}S||} \right] . \quad (35)$$



Also using (34) for the factor  $\frac{||\underline{\delta\psi}_c^{(1)}||}{||\underline{\psi}^{(2)}||}$  in (28) provides the bound

$$\frac{||\underline{\delta\psi}_c^{(1)}||}{||\underline{\psi}^{(2)}||} \leq \frac{||D-E|| \cdot ||\underline{\delta\psi}_c^{(1)}||}{||\underline{q}|| \cdot (1 - ||(D-E)^{-1}S||)} \quad (36)$$

Now applying (34), (35), and (36) to (28) produces

$$\frac{||\underline{\delta\psi}^{(2)}||}{||\underline{\psi}^{(2)}||} \leq \frac{\nu}{1-\nu \cdot \frac{||\underline{\delta D}-\underline{\delta E}||}{||D-E||}} \left\{ \frac{||\underline{\delta E}-\underline{\delta D}||}{||D-E||} + \frac{1}{[1 - ||(D-E)^{-1}S||]} \left[ \frac{||\underline{\delta S}||}{||D-E||} \cdot \frac{\rho(1+\nu - ||(D-E)^{-1}S||)}{||(D-E)^{-1}S||} \right. \right. \\ \left. \left. + \frac{||S+\underline{\delta S}||}{||\underline{q}||} \cdot ||\underline{\delta\psi}_c^{(1)}|| + \frac{||\underline{\delta q}||}{||\underline{q}||} \right] \right\} \quad (37)$$

where

$$\rho = ||(D-E)^{-1}S|| \cdot ||[(D-E)^{-1}S]^{-1}|| \quad (38)$$

is the condition number of the iteration matrix.

The General Iterate

Suppose the  $i^{th}$  iteration has been completed. That is,  $\underline{\psi}_c^{(i)} = \underline{\psi}^{(i)} + \underline{\delta\psi}_c^{(i)}$  has been computed. A bound on the relative uncertainty in the  $i+1^{st}$  iterate solution can be derived from recognizing that instead of solving the system

$$(D-E)\underline{\psi}^{(i+1)} = S\underline{\psi}_c^{(i)} + \underline{q} \quad (39)$$

the machine solves the perturbed system

$$(D+\underline{\delta D}-E-\underline{\delta E})(\underline{\psi}^{(i+1)} + \underline{\delta\psi}^{(i+1)}) = (S+\underline{\delta S})(\underline{\psi}_c^{(i)} + \underline{\delta\psi}_c^{(i)}) + (\underline{q} + \underline{\delta q}) \quad (40)$$

Proceeding in the same fashion as in the previous section,



$$\frac{||\underline{\psi}^{(i+1)}||}{||\underline{\psi}^{(i+1)}||} \leq \frac{v}{1-v \cdot \frac{||\delta D - \delta E||}{||D-E||}} \left\{ \frac{||\delta E - \delta D||}{||D-E||} + \frac{||\delta S||}{||D-E||} \cdot \frac{||\underline{\psi}^{(i)}||}{||\underline{\psi}^{(i+1)}||} + \frac{||S + \delta S||}{||D-E||} \cdot \frac{||\underline{\psi}_c^{(i)}||}{||\underline{\psi}^{(i+1)}||} + \frac{||\delta q||}{||D-E|| \cdot ||\underline{\psi}^{(i+1)}||} \right\} . \quad (41)$$

From equation (39),

$$\underline{\psi}^{(i+1)} = (D-E)^{-1} S \underline{\psi}_c^{(i)} + (D-E)^{-1} \underline{q}$$

or

$$\underline{\psi}_c^{(i)} = \left[ (D-E)^{-1} S \right]^{-1} \left[ \underline{\psi}^{(i+1)} - (D-E)^{-1} \underline{q} \right] .$$

Consequently

$$\frac{||\underline{\psi}_c^{(i)}||}{||\underline{\psi}^{(i+1)}||} \leq \left\| \left[ (D-E)^{-1} S \right]^{-1} \right\| \cdot \left[ 1 + \frac{|| (D-E)^{-1} || \cdot || \underline{q} ||}{||\underline{\psi}^{(i+1)}||} \right] \quad (42)$$

The factor  $\frac{1}{||\underline{\psi}^{(i+1)}||}$  on the R.H.S. of (42) can be bounded by recalling that the unperturbed system obeys

$$\underline{\psi}^{(i+1)} = \sum_{m=0}^i A^m (D-E)^{-1} \underline{q} \quad (43)$$

where for convenience of notation

$$A = (D-E)^{-1} S . \quad (44)$$

Consequently

$$\underline{q} = (D-E) \left[ I + A + A^2 + \dots + A^i \right]^{-1} \underline{\psi}^{(i+1)} .$$



But if condition (33) is met,

$$(I-A)^{-1} = \sum_{m=0}^{\infty} A^m$$

so

$$\begin{aligned} [I+A+A^2+\dots+A^i] &= [(I-A)^{-1} - A^{i+1} - A^{i+2} - \dots]^{-1} \\ &= [(I-A)^{-1} - A^{i+1}(I+A+A^2+\dots)]^{-1} \\ &= [(I-A^{i+1})(I-A)^{-1}]^{-1} \\ &= (I-A)(I-A^{i+1})^{-1}. \end{aligned}$$

Hence

$$q = (D-E)(I-A)(I-A^{i+1})^{-1}\underline{\psi}^{(i+1)}.$$

Consequently

$$||\underline{q}|| \leq \frac{||D-E|| \cdot (1+||A||) \cdot ||\underline{\psi}^{(i+1)}||}{1 - ||A^{i+1}||} \quad (45)$$

due to Theorem 2 if

$$||A^{i+1}|| < 1$$

which is certainly true if condition (33) is met. Since

$$||A^{i+1}|| \leq ||A||^{i+1} < 1,$$

$$1 - ||A^{i+1}|| \geq 1 - ||A||^{i+1}$$





and

$$\frac{1}{1 - ||A^{i+1}||} \leq \frac{1}{1 - ||A||^{i+1}} \quad (46)$$

Using (46), inequality (45) becomes

$$||\underline{q}|| \leq \frac{||D-E|| \cdot (1 + ||A||) \cdot ||\underline{\psi}^{(i+1)}||}{1 - ||A||^{i+1}}$$

or in terms of the iteration matrix norm

$$\frac{1}{||\underline{\psi}^{(i+1)}||} \leq \frac{||D-E|| \cdot [1 + ||(D-E)^{-1}S||]}{||\underline{q}|| \cdot [1 - ||(D-E)^{-1}S||^{i+1}]} \quad (47)$$

Applying (47) to the R.H.S. of (42) gives

$$\frac{||\underline{\psi}_c^{(i)}||}{||\underline{\psi}^{(i+1)}||} \leq \frac{\rho}{|| (D-E)^{-1}S ||} \left[ \frac{1 + \nu (1 + ||(D-E)^{-1}S||) - ||(D-E)^{-1}S||^{i+1}}{1 - ||(D-E)^{-1}S||^{i+1}} \right] \quad (48)$$

Now applying (47) and (48) to (41) produces

$$\begin{aligned} \frac{||\underline{\delta\psi}^{(i+1)}||}{||\underline{\psi}^{(i+1)}||} &\leq \frac{\nu}{1 - \frac{\nu \cdot ||\delta D - \delta E||}{||D-E||}} \left\{ \frac{||\delta E - \delta D||}{||D-E||} + \frac{1}{1 - ||(D-E)^{-1}S||^{i+1}} \left[ \frac{||\delta S||}{||D-E||} \cdot \frac{\rho [1 + \nu (1 + ||(D-E)^{-1}S||) - ||(D-E)^{-1}S||^{i+1}]}{|| (D-E)^{-1}S ||} \right. \right. \\ &\quad \left. \left. + \frac{||S + \delta S||}{||\underline{q}||} \cdot [1 + ||(D-E)^{-1}S||] \cdot ||\underline{\psi}_c^{(i)}|| + [1 + ||(D-E)^{-1}S||] \cdot \frac{||\delta q||}{||\underline{q}||} \right] \right\} \quad (49) \end{aligned}$$

This expression is valid for  $i = 2, 3, \dots$ .

### Analysis of Error Bound

Observe that in expression (49), the only terms which are affected by the number of iterations are  $|| (D-E)^{-1}S ||^{i+1}$  and  $\frac{1}{1 - || (D-E)^{-1}S ||^{i+1}}$ . As  $i$  increases, the former magnifies



the bound slightly and the latter diminishes the bound. The latter effect is predominant. Therefore the bound becomes tighter as iteration proceeds and roundoff error propagation is diminished. This effect is not strong enough to force the relative uncertainty to vanish, however, as  $i$  approaches  $\infty$ .

Certain terms and factors in (49) can be neglected with respect to more dominant quantities in order to obtain a qualitative view of the bound. That is,

$$\frac{||\delta\psi^{(i+1)}||}{||\psi^{(i+1)}||} \leq \frac{\nu}{1 - \frac{\nu \cdot ||\delta D - \delta E||}{||D - E||}} \left\{ \frac{||\delta E - \delta D||}{||D - E||} + \frac{||\delta S||}{||D - E||} \cdot \frac{\rho \nu}{||(D - E)^{-1} S||} + \frac{||S + \delta S||}{||q||} \cdot \frac{||\delta\psi_c^{(i)}||}{||q||} + \frac{||\delta q||}{||q||} \right\} \quad (50)$$

contains the dominant quantities in (49).

The condition of the matrix  $(D - E)$  has a dominant role in the roundoff error bound. If  $\nu$  is very large, the relative uncertainty in the iterate solution will be significant. If  $\nu$  is large enough that the factor  $\frac{\nu \cdot ||\delta D - \delta E||}{||D - E||}$  is close to unity, the relative uncertainty can be extremely large. For this to occur,  $\nu$  would have to be of the order of  $10^{14}$  for the double precision mode, extremely ill-conditioned. This event is unlikely. Since  $\nu$ , which is always greater than unity, appears to the second power in (50), it is the dominant quantity in the bound.

The condition number of the iteration matrix,  $\rho$ , also plays an important part in the roundoff error bound. Its effect is subordinate to that of  $\nu$  since  $\rho$  appears only to the first power. But if  $(D - E)^{-1} S$  and  $(D - E)$  are both



ill-conditioned, the quantity  $v^2 \rho$  could cause significant roundoff error propagation in the solution.

The error bounds derived here display another important effect. Expressions (25), (37), and (49) each contain the uncertainty  $||\delta D - \delta E||$  in important positions. This can cause the exact cancellation of roundoff errors during the iterative process. That is,  $||\delta D - \delta E||$  vanishes. This gives vivid corroboration to Isaacson's observation quoted previously. The presence of  $||\delta D - \delta E||$  in the dominating factor  $\frac{v}{1 - \frac{v \cdot ||\delta D - \delta E||}{||D - E||}}$  reduces it to  $v$  when exact cancellation occurs. This effect is also felt through the term  $\frac{||\delta E - \delta D||}{||D - E||}$ .

Observe that each term in the braces of (49) has a multiplier which is extremely small. That is  $\delta E$ ,  $\delta D$ ,  $\delta S$ ,  $\delta q$ , and  $\delta \psi_c^{(i)}$  are all of the order of the machine unit roundoff error. The factor  $||\underline{q}||$  is generally on the order of unity. From equations (23), (24), (25), and (26) of Chapter II, the infinity norm of  $S$  is

$$\begin{aligned} ||S|| &= \frac{2\sigma^s}{4} \sum_{n=1}^N \omega_n \\ &= \sigma^s . \end{aligned} \tag{51}$$

From equations (16c), (16d), (21), and (22) of Chapter II, the infinity-norm of  $(D-E)$  is



$$\begin{aligned}
 ||D-E|| &= \max_j \{ |e_j| + d_j \} \\
 &= \max_j \frac{2|\mu_j|}{\Delta} \\
 &= \frac{2|\mu_j|_{\max}}{\Delta} .
 \end{aligned} \tag{52}$$

As a consequence of the above facts, the quantity

$$\frac{v^2 \rho}{1 - v \cdot ||\delta D - \delta E||}$$

must be of the order of  $10^{14}$  for the relative uncertainty to be significant. Assuming that  $||\delta D - \delta E|| = 0$  and  $\rho \approx v$ , this means that

$$v^3 \approx 10^{14}$$

or

$$v \approx 10^5$$

before significant roundoff error is propagated to the iterate solution. These extremely large condition numbers simply do not exist for physical problems of interest in the application of the  $S_N$  method.

### Estimating the Condition Numbers

The condition number of the iteration matrix is not readily estimated. Although the infinity-norm of  $(D-E)^{-1}S$  can be calculated precisely, as discussed in Chapter II, calculation of  $||[(D-E)^{-1}S]^{-1}||$  is not tractable.





Consequently an estimate of  $\rho$  is not available nor is an upper bound on it. The following discussion assumes that  $\rho$  is small enough that its influence on the roundoff error bound is less than that of  $v$ .

Estimation of  $v$  is possible. Equations (27) and (28) in Chapter II reveal that the infinity norm of  $(D-E)^{-1}$  is

$$|| (D-E)^{-1} || = \max_j \left\{ \frac{1}{d_j} \left[ 1 + \left( \frac{|e_j|}{d_j} \right) + \left( \frac{|e_j|}{d_j} \right)^2 + \dots + \left( \frac{|e_j|}{d_j} \right)^{R-1} \right] \right\} \quad (53a)$$

or

$$|| (D-E)^{-1} || = \frac{1}{d_i} \left[ \frac{1-\beta^R}{1-\beta} \right] \quad (53b)$$

where  $R$  is the number of equi-spaced spatial intervals,  $\Delta$ , and

$$0 \leq \beta = \frac{|e_i|}{d_i} < 1. \quad (54)$$

Here

$$e_i = \frac{2|\mu_j|_{min} - \Delta\sigma^t}{2\Delta} \quad (55a)$$

and

$$d_i = \frac{2|\mu_j|_{min} + \Delta\sigma^t}{2\Delta}. \quad (55b)$$

From (53),

$$|| (D-E)^{-1} || < \frac{1}{d_i(1-\beta)} = \frac{1}{\sigma^t}. \quad (56)$$



Consequently from (52) and (53)

$$\nu = \frac{2 |\mu_j|_{\max}}{\Delta \bar{d}_i} \left[ \frac{1 - \beta^R}{1 - \beta} \right] \quad (57)$$

where  $i$  is the index for the minimum absolute ordinate in the set  $\{\mu_j\}$ .

A tight bound on  $\nu$  can be obtained by neglecting  $\beta^R$ . That is,

$$\nu < \frac{2 |\mu_j|_{\max}}{\Delta \sigma^t} .$$

Since all problems must have  $|\mu_j|_{\max} < 1$ ,

$$\nu < \frac{2}{\Delta \sigma^t} \quad (58)$$

is a useful estimator for  $\nu$ . For the problems considered in Chapter II,  $\sigma^t = 1.0 \text{ cm}^{-1}$  and  $\Delta = 1/3 \text{ cm}$  so

$$\nu < 6 . \quad (59)$$

Hence (D-E) is a very well-conditioned matrix for the problem considered. Consequently roundoff error propagation was insignificant in the investigations conducted. In practice, roundoff error propagation has not been experienced by this investigator which renders the  $S_N$  algorithm unstable. This must be a consequence of the well-conditioned state of the matrices  $(D-E)^{-1}S$  and (D-E) as well as to the roundoff error cancellation property of the iterative method.



## Effect of Exponential Transform

The presentation in Chapter III reveals that the transform

$$\psi_j(x) = \phi_j(x) e^{\alpha x} \quad (60)$$

applied to the  $S_N$  equations, produces an iterative algorithm with the same form as that of the unmodified  $S_N$  algorithm but with a modified source and a different iteration matrix,  $(D-E)^{-1}S$ . As a consequence, the roundoff error analysis, previously presented, carries over into the transform domain in its entirety. That is, expressions (25), (37), and (49) are valid for

$$\frac{||\delta\phi^{(i+1)}||}{||\phi^{(i+1)}||}$$

if  $(D-E)$  and  $(D-E)^{-1}S$  are replaced by  $(D-E)$  and  $(D-E)^{-1}S$  respectively and  $q$  is replaced by its transformed counterpart. All of the above quantities are defined in Chapter III.

From equations (18) and (19) of Chapter III it is clear that

$$||(D-E)|| = ||(D-E)|| \quad (61)$$

since terms involving  $\alpha$  cancel. From equations (23) and (24) of Chapter III,

$$||(D-E)^{-1}|| = \frac{1}{d_i} \left[ \frac{1-\gamma^R}{1-\gamma} \right] \quad (62)$$



where

$$0 \leq \gamma = \frac{|e_i|}{d_i} < 1 \quad (63)$$

and

$$e_i = \frac{2|\mu_j|_{min} - \Delta\sigma^t - \Delta\alpha|\mu_j|_{min}}{2\Delta} \quad (64a)$$

$$d_i = \frac{2|\mu_j|_{min} + \Delta\sigma^t + \Delta\alpha|\mu_j|_{min}}{2\Delta} . \quad (64b)$$

Observe that in problems for which the transform method is effective, i.e.  $e_j \geq 0$  for all  $j$ , and

$$\frac{1}{d_j} < \frac{1}{d_j} \quad (65)$$

of equation (55b) and

$$\gamma < \beta \quad (66)$$

of equation (54). Since  $\frac{1}{d_i}$  is the predominant factor in (62),

$$||(\mathcal{D}-E)^{-1}|| < ||(D-E)^{-1}|| . \quad (67)$$

Consequently the condition number of  $(\mathcal{D}-E)$  is smaller than the condition number of  $(D-E)$ . As previously discussed, the condition number of this matrix is the predominant factor in the stability of the iterative algorithm. Consequently it is expected that the transform domain iterative algorithm is "better" conditioned than the unmodified  $S_N$  algorithm.





## CHAPTER VI

### CONCLUSIONS

The  $S_N$  algorithm in one-dimensional plane geometry has been formulated within a mathematical framework which allows detailed insight into its convergence properties. Knowledge of these properties permits the derivation of an improved convergence criterion which, if met, guarantees that the fractional iterative error is arbitrarily small. Utilization of this criterion,

$$\frac{||\frac{\delta^{(i+1)}}{\psi_k^{(i)}}||}{\psi_k} < \frac{\epsilon}{1-\epsilon} [1 - ||(D-E)^{-1}S||] \quad (1)$$

is especially important in problems for predominantly scattering media for which  $||(D-E)^{-1}S||$  is close to unity.

The matrix formulation of the iterative  $S_N$  algorithm allows calculation of the infinity-norm of the iteration matrix,  $||(D-E)^{-1}S||$ , for homogeneous media problems in which scattering is isotropic in the Laboratory Coordinate System. Imposing the condition

$$||(D-E)^{-1}S|| < 1 \quad (2)$$

leads to sufficient conditions for which convergence of the  $S_N$  algorithm is guaranteed. These conditions impose



constraints on the values used for the numerical quantities of the problem,  $\Delta$ ,  $|\mu_j|_{min}$ ,  $\sigma^s$ , and  $\sigma^t$ . The constraint

$$\Delta < \frac{|\mu_j|_{min}}{\sigma^s} \quad (3)$$

is sufficient to guarantee convergence and allows a limited amount of negativity in the matrix elements of the iteration matrix. The constraint

$$\Delta < \frac{|\mu_j|_{min}}{\sigma^t} \quad (4)$$

renders the iteration matrix non-negative and is sufficient to guarantee convergence for all physically realizable problems. The solution for such a system is non-negative for non-negative sources.

A spatial transform of the type

$$\psi_j(x) = \phi_j(x) \phi^\alpha(x) \quad (5)$$

was used on a special half-range problem. This transform places the acceleration parameter,  $\alpha$ , in positions within the iteration matrix such that each non-zero matrix element is reduced. This diminishes the norm of the iteration matrix and accelerates convergence of the  $S_N$  algorithm. Reductions of almost 25% in the number of iterations to convergence have been realized for sample problems using the exponential transform

$$\psi_j(x) = \phi_j(x) e^{\alpha x} \quad (6)$$



where  $\alpha > 0$ . A practical maximum value of  $\alpha$  for this transform was found to be

$$\alpha^* = \frac{2(\mu_j)_{min}^{-\Delta\sigma^t}}{\Delta(\mu_j)_{min}}. \quad (7)$$

A practical useful value of  $\alpha$  is much smaller than  $\alpha^*$  and is chosen as a compromise between the user's estimate of tolerable discretization error and the reduction in calculational effort. It is possible that  $S_N$  problems in higher dimensional geometries can be formulated in the mathematical context displayed in this investigation for plane geometry. If transforms can be found which leave the angular discretized  $S_N$  equations invariant and reduce the norm of the iteration matrix, vast savings of computational effort can be realized for these problems. Possible transform candidates are some form of the integrating factor for the angular discretized equations describing the problem after neglecting the scattering gain term.

Nothing done here suggests that a transform can be found which is useful for all problems in a particular geometry. Experience of this investigator indicates that it is more likely that each problem in the geometry has a "best" transform which can be prescribed based upon the source, boundary conditions, and the prescriber's estimate of the form of the solution.

The spatial discretization error in the  $S_N$  algorithm is proportional to the second derivative of the solution  $\psi_j(x)$ . The spatial transform



$$\psi_j(x) = \phi_j(x) e^{-\alpha x} \quad (8)$$

with  $\alpha > 0$  was used on a one-dimensional problem to decrease the discretization error. Discretization errors are shown to decrease because the  $\phi$ -domain solution has less curvature magnitude than the unmodified  $S_N$   $\psi$ -domain solution.

The transform used to decrease discretization errors must be tailored to each individual problem. The choice of a successful transform for a specific problem must be based on intuition developed for that problem by experience, knowledge of analytic solutions to similar problems, or guess. A possible candidate is some variation of the integrating factor for the problem.

An upper bound was derived for the relative uncertainty in the iterate solution of the  $S_N$  algorithm due to roundoff errors. This bound is expressed in terms of the condition numbers of the matrices  $(D-E)$  and  $(D-E)^{-1}S$ . The bound reveals that roundoff error cancellation can occur in the iterative process due to the factor  $||\delta D - \delta E||$ . If cancellation does not occur, however, roundoff errors can be magnified during the iterative process if the matrices  $(D-E)^{-1}S$  and  $(D-E)$  are extremely ill-conditioned. Such an event is improbable. The bound on the fractional uncertainty for the iterate solution diminishes as iteration proceeds. It does not, however, vanish in the limit of an infinite number of iterations.





For the problems treated here,  $(D-E)$  is well-conditioned and its condition number is calculable from the problem parameters. The condition number of the iteration matrix is not calculable because  $||[(D-E)^{-1}S]^{-1}||$  is not calculable. In the problems treated here, propagation of roundoff error was not significant.



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## APPENDIX A

FULL-RANGE  $S_N$  PROGRAM AND SAMPLE OUTPUT



```

C THIS PROGRAM IMPLEMENTS THE LAGGE-ORBITAL ADDITION TO SOLVE
C THE SLAB PROBLEM WITH A DIFFUSE SOURCE.
C THE VARIABLES EMPLOYED ARE:
C A=WIDTH OF SLAB IN CM.
C N=NUMBER GIVING THE NUMBER OF SPATIAL SECTIONS.
C NSECT=NUMBER OF SPACE FILL POINTS, INCLUDING BOTH BOUNDARIES.
C SIGMA=TOTAL COLLISION CROSS SECTION IN UNITS 1/CM.
C SIGMAS=RADIATION SCATTERING CROSS SECTION IN UNITS 1/CM.
C *EIGHT(J)=WEIGHTS OF THE RADIATION SAT.
C MU(J)=DISCRETE SET OF ABSORPTION COEFFICIENTS OF ANGLE JTH
C RESPECT TO THE X-AXIS.
C PHI(K,J)=DIRECTIONAL FLUX AT SPATIAL POINTS A(I) DESCRIBING
C NEUTRONS GOING IN DIRECTION MU(J).
C MIDSOR(K,J)=TOTAL SOURCE TERM EVALUATED AT SPATIAL MIDPOINTS
C AND MU(J). COMPOSED OF SCATTERING TERM PLUS
C THE EXTERNAL SOURCE.
C MIDPHI(K,J)=DIRECTIONAL FLUX CALCULATED AT SPATIAL MIDPOINTS
C DETERMINED BY ONE PASSAGE ITERATION OF PHIK(J)
C AND USED TO CALCULATE NEXT ITERATE SCATTERING
C SOURCE TERM.
C SOURCE(K,J)=EXTERNAL SOURCE AT SPATIAL MIDPOINTS AND MU(J).
C THIS TERM DOES NOT CHANGE WITH EACH ITERATION.
C ZPS=CONVERGENCE CRITERION USED FOR FRACTURAL DIFFERENCES.
C EPSI=UPPER BOUND ON THE FRACTURAL ERROR.
C MAXIMUMP=MAXIMUM NORM OF THE ITERATION MATRIX.
C Z(J)=MATRIX ELEMENT OF (Z-E) CORRESPONDING TO MU(J).
C JJ(J)=MATRIX ELEMENT OF (J-E) CORRESPONDING TO MU(J).
C
C INTEGER N
C REAL*8 MU(6),MIDSOR(30,6),MIDPHI(30,6),ZPSN
C DOUBLE PRECISION PHIK(31,6),SIGMA(30,6),SIGMAS,SIGMASA,
C *EIGHT(6),ADJUSTA,ZPS,EPSI,SUMZ,A(31),CELSH(11,9),
C TCCSN,D(6),E(6),EPS,WTS,WTS1
C COMMON /SOURCE/PHI,K,MJ
C EPSI=C.0001
C PSH=C.0001
C Z=10.0
C ZPS=.30
C N=N+1
C SIGMA=1.0
C SIGMAS=0.5
C MU(1)=-.7462
C MU(4)=-.66121
C MU(3)=-.93247
C MU(4)=-.23362
C MU(5)=-.66121
C MU(6)=-.93247
C *EIGHT(1)=.46791
C *EIGHT(2)=.36076
C *EIGHT(3)=.17132
C *EIGHT(4)=.46791
C *EIGHT(5)=.36076
C *EIGHT(6)=.17132
C CELSA=VR
C THIS PART OF THE PROGRAM CALCULATES THE ALGEBRAIC COEFFICIENTS.

```



```

0029 DO 30 I=1,2
0030   Z(I)=(2.*XU(I)-DELTA*SIGMA)/(2.*DELTA)
0031   U(I)=(2.*XU(I)+DELTA*SIGMA)/(2.*DELTA)
0032   J=3*I
0033   Z(J)=Z(I)
0034   U(J)=U(I)
0035 C THIS PART OF THE PROGRAM COMPUTES THE NORM OF THE ITERATION
0036 C VECTOR. TO BE VALID NU(I) MUST BE THE MINIMUM ABSOLUTE
0037 C VALUE OF THE COMPONENTS OF THE DIRECTION SET.
0038 J=N-3
0039   SUM=X(1)/D(1)
0040   SUM1=1.
0041   SUM2=0.
0042 DO 40 I=1,J
0043   SUM1=SUM1+SUM
0044   SUM2=SUM2+SUM1
0045   SUM1=SUM1+SUM
0046   SUM2=SUM2+SUM1
0047   SUM=SIGN(SUM2/4.*(4./D(I)*(1.+SUM2)+3./D(I)*SUM1)
0048 C THIS PART OF PROGRAM CALCULATES THE ALGORITHM CONVERGENCE
0049 C CRITERION.
0050   EPS=EPS1/(1.-EPS1)*(1.-NORM)
0051 DO 50 I=1,3
0052   A(I)=(I-1)*DELTA
0053 DO 60 J=1,6
0054   DO 70 K=1,8
0055     SOURCE(K,J)=1.0
0056     MISCOR(K,J)=1.0
0057 DO 85 J=1,6
0058   DO 95 K=1,8
0059     P2=(X(J)-C.
0060 C THIS PART OF THE PROGRAM STARTS THE INNER ITERATION. NOIS
0061 C THAT THE INITIAL FLUX VECTOR GUESS IS THE ZERO VECTOR.
0062 DO 312 INNER=1,1000
0063 DO 175 J=1,3
0064 DO 150 K=2,N
0065 IF (K.EQ. 2) PHI(2,J)=1./D(J)*MISCOR(1,J)
0066 IF (K.EQ. 2) GO TO 150
0067 PHI(K,J)=E(C)/D(J)*PHI(K-1,J)+1./D(J)*MISCOR(K-1,J)
0068 CONTINUE
0069 CONTINUE
0070 DO 190 J=4,6
0071 DO 185 K=1,8
0072   N=N-K
0073 IF (N.EQ. (N-1)) PHI(N,J)=1./D(J)*MISCOR(N,J)
0074 IF (K.EQ. (K-1)) GO TO 185
0075 PHI(N,J)=E(J)/D(J)*PHI(N+1,J) + 1./D(J)*MISCOR(N,J)
0076 CONTINUE
0077 CONTINUE
0078 C THIS LOOP COMPUTES THE NEW SPATIAL AND-TIME FLUXES FROM THE PRESENT
0079 C ITERATE FLUXES.
0080 DO 230 J=1,6
0081 DO 230 K=1,8
0082   MISCOR(K,J) = ( PHI(K+1,J) + PHI(N,J) ) / 2.
0083 C CHECK FOR POINTWISE CONVERGENCE IS CONDUCTED.
0084 C NO CONVERGENCE CHECK IS MADE THE FIRST TIME THROUGH.

```





```

0069 IF (XNNEZ.EQ. 1) GO TO 480
0070 C A TABLE SEARCH IS CONDUCTED FOR THE MAXIMUM DIFFERENCE.
0071 SUM=0.
0072 DO 260 J=1,N
0073 SUM=PHI(K,J)-OLDPHI(K,J)
0074 IF(SUM.GT. SUM) SUM=SUM+1
0075 CONTINUE
0076 DO 265 N=2,M
0077 SUM=SUM/OLDPHI(K,J)
0078 IF(CNV.GT. EPS) GO TO 280
0079 CONTINUE
0080 DO 270 J=1,N
0081 SUM=SUM/OLDPHI(K,J)
0082 IF(CNV.GT. EPS) GO TO 280
0083 CONTINUE
0084 GO TO 600
0085 CONTINUE
0086 C THIS LOOP CALCULATES THE NEW SOURCE.
0087 DO 290 K=1,N
0088 DO 290 J=1,N
0089 SUM=0.
0090 DO 295 I=1,N
0091 SUM=SUM+DELTA(I)*SIEPHI(K,I)
0092 MIDSUM(K,J)=SUM*5/2.* SUM1 + SOURCE(K,J)
0093 DO 295 I=1,N
0094 DO 295 J=1,N
0095 OLDPHI(K,J)=PHI(K,J)
0096 CONTINUE
0097 PHIE(0,010)
0098 FORMAT(1,'5X,THE UNMODIFIED DISCRETE ORIGINATES ',
0099 1,'ALGORITHM' RESULTS ARE LISTED BELOW FOR THE FOLLOWING',
0100 1,' POWERED CHARACTER')
0101 PHIE(0,020) *SIEPHI, *SOURCE, *
0102 FORMAT(1,'5X, *SIEPHI=2.1, *CM*/20X, *TOTAL ',
0103 1,' *ACROSS *CROSS SECTION', *6.4, *1/CM*/20X, *SCATTERI',
0104 1,' *MACROSCOPIC *CROSS SECTION', *6.4, *1/CM*/20X,
0105 1,' *NUMBER OF *SPATIAL *MESH INCREMENTS', *13, *')
0106 PHIE(0,025) DELTA
0107 FORMAT(1,'5X, *DELTA', *SIDE OF EACH SPATIAL MESH INCREMENT=',
0108 1,' *7.5, *CM*/20X, *ANALYTICAL *QUADRATURE SET USED= *SIX ',
0109 1,' *ORDINATE *CROSS-SECTION', *1/20X, *SOURCE= *UNIFORM',
0110 1,' *WITH *ALL *SIEPHI *')
0111 PHIE(0,030) EPS, *EPSI, *EPSI
0112 FORMAT(1,'5X, *THE *FRACTIONAL *DIFFERENCE *CONVERGENCE',
0113 1,' *6000, *12.2, *AS SET AFTER *15, *ITERATIONS',
0114 1,' *THIS *LABELS *1/5X, *THE *FRACTIONAL *ITERATION',
0115 1,' *BEFORE IS *LESS *THAN *7.6, *')
0116 SUM=SUM/2(01)
0117 SUM1=1/2(01)
0118 PHIE(0,040) *NEW *SUM *SUM1
0119 FORMAT(1,'5X, *THE *INFINITE *NO. OF *THE *ITERATION',
0120 1,' *MACRO', *27.5, *BASED ON *THE *VALUES OF *E(I)/2(01)=',

```



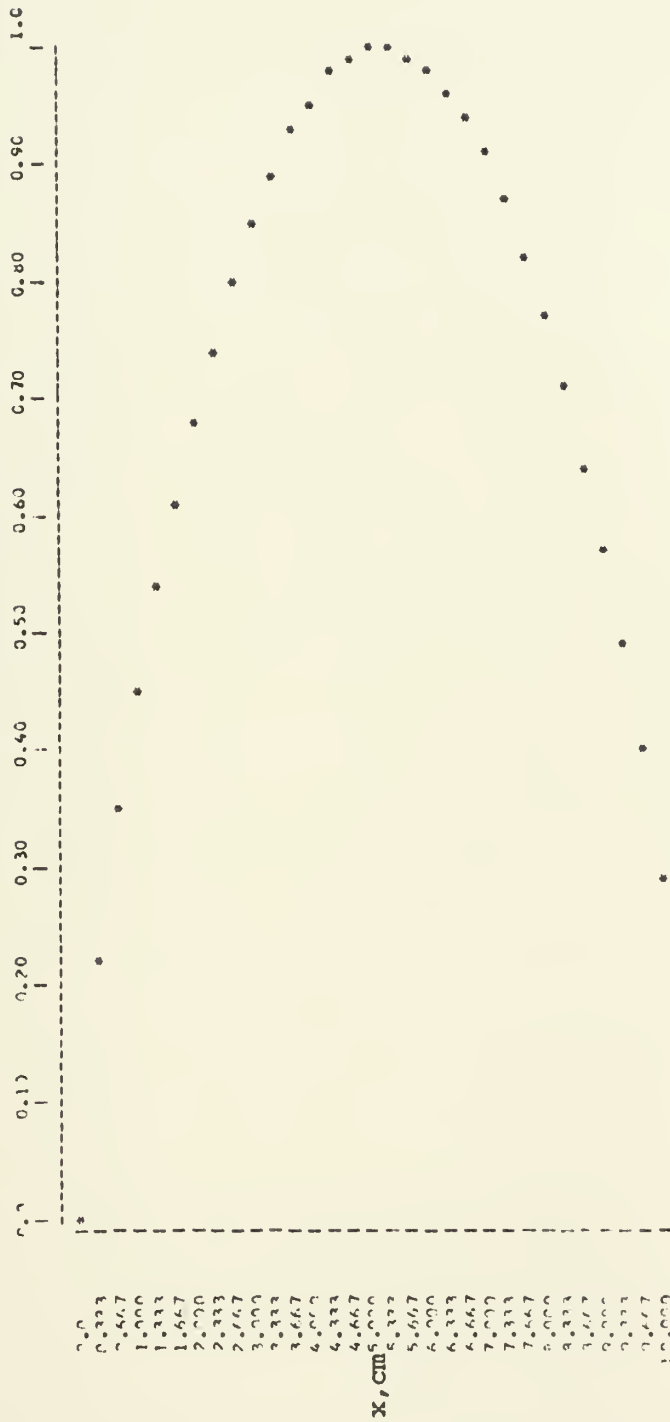








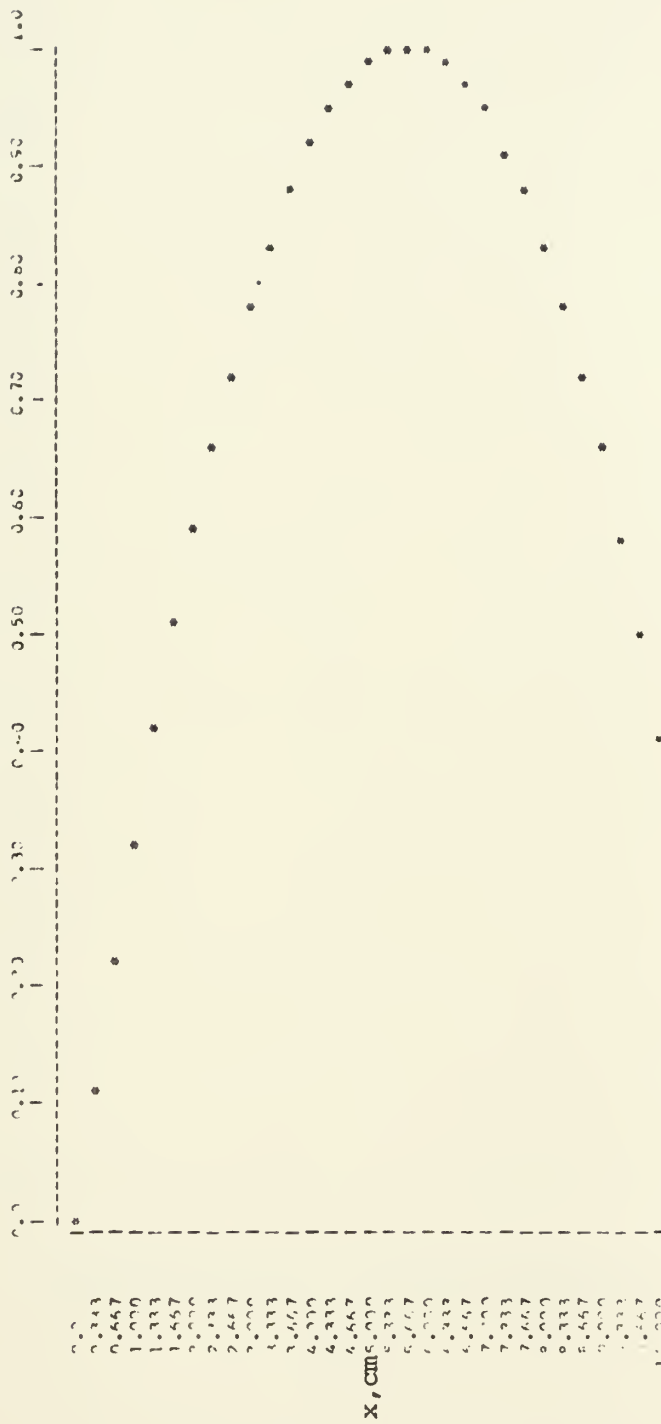
NORMALIZED ANGULAR FLUX VS. SLAB POSITION  
FOR DIRECTION MJ= 0.2386



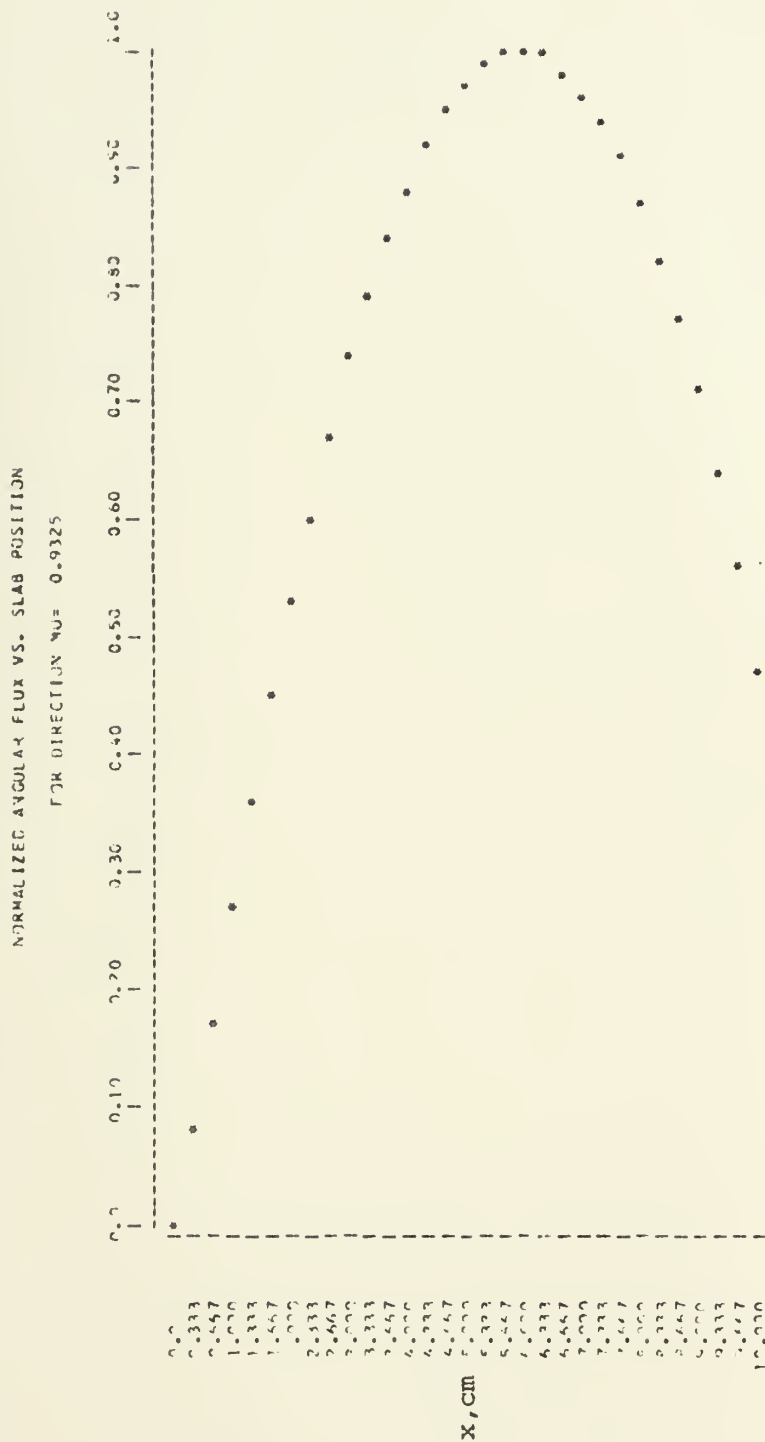




NORMALIZED ANGULAR FLUX VS. SLAB POSITION  
FOR DIRECTION MU= 0.6612

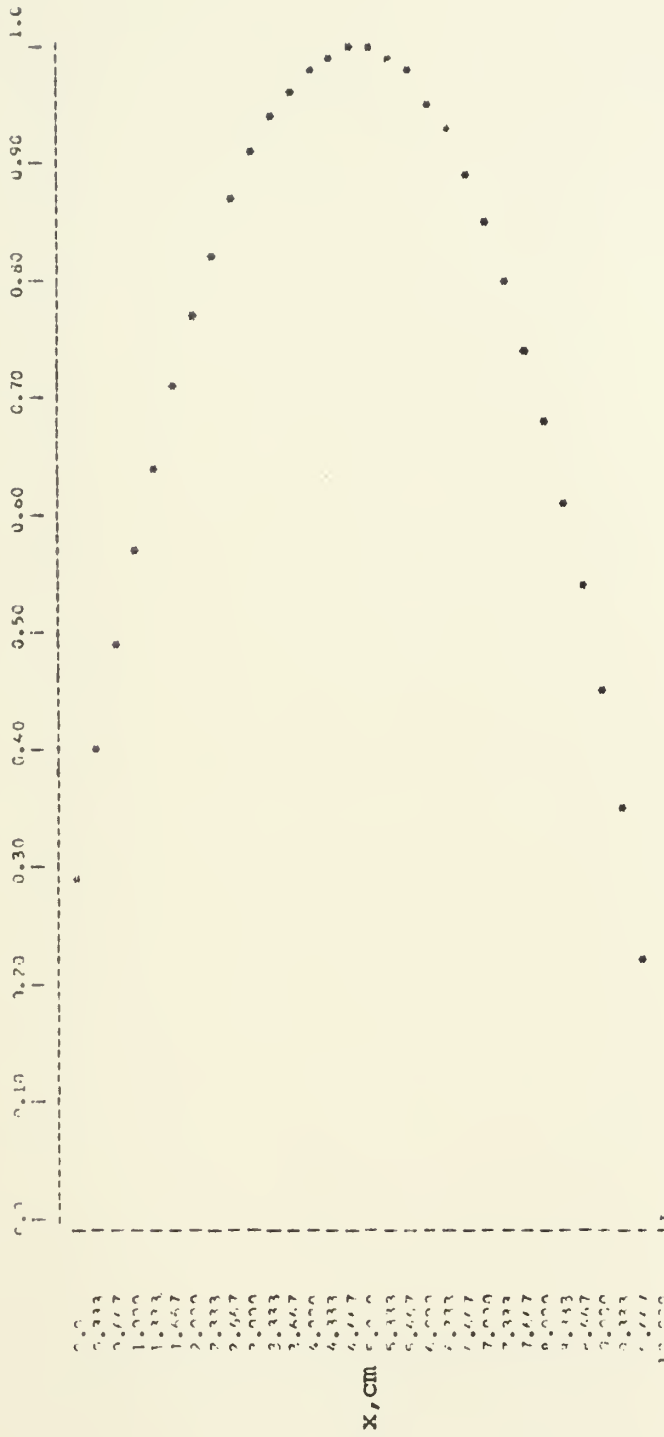




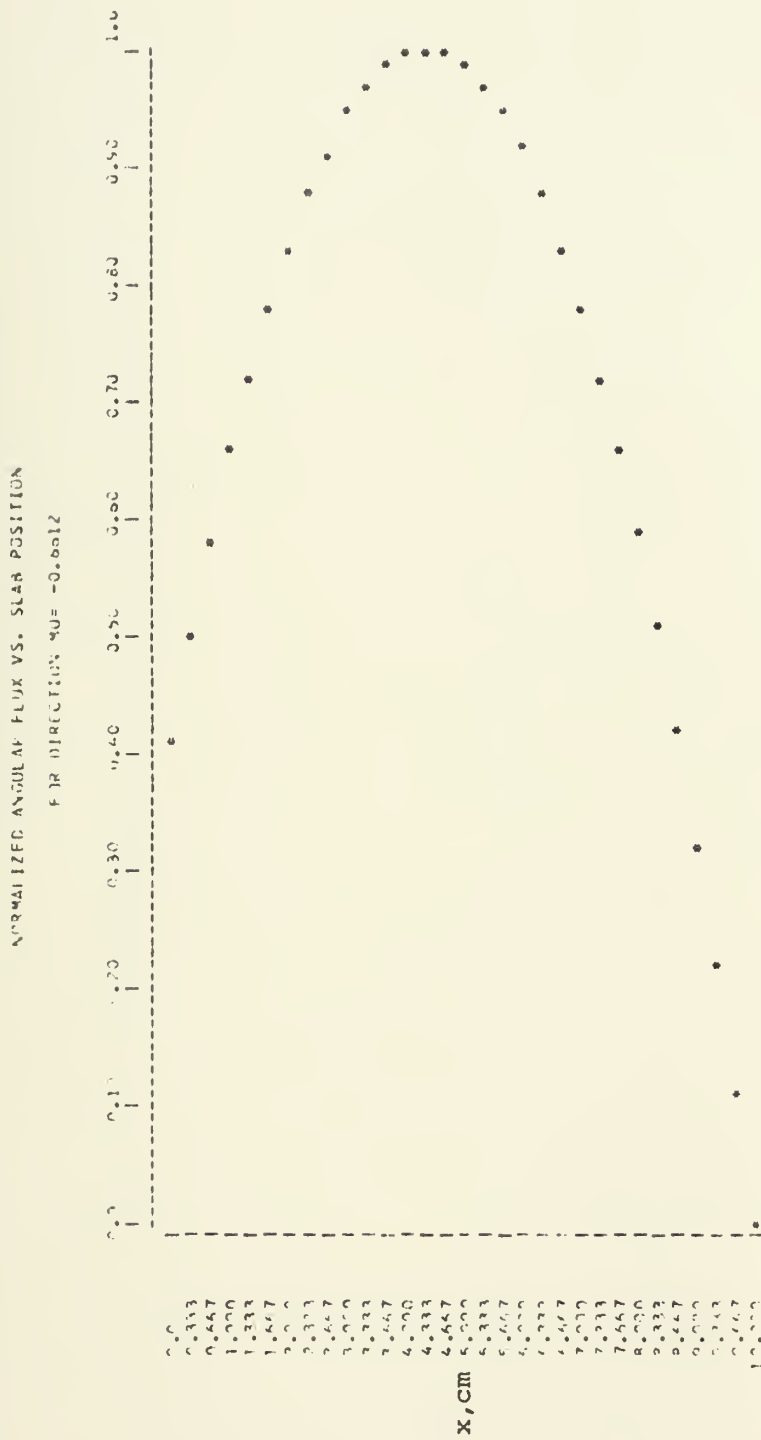




NORMALIZED ANGULAR FLUX VS. SLAB POSITION  
FOR DIRECTION  $\mu = -0.2336$



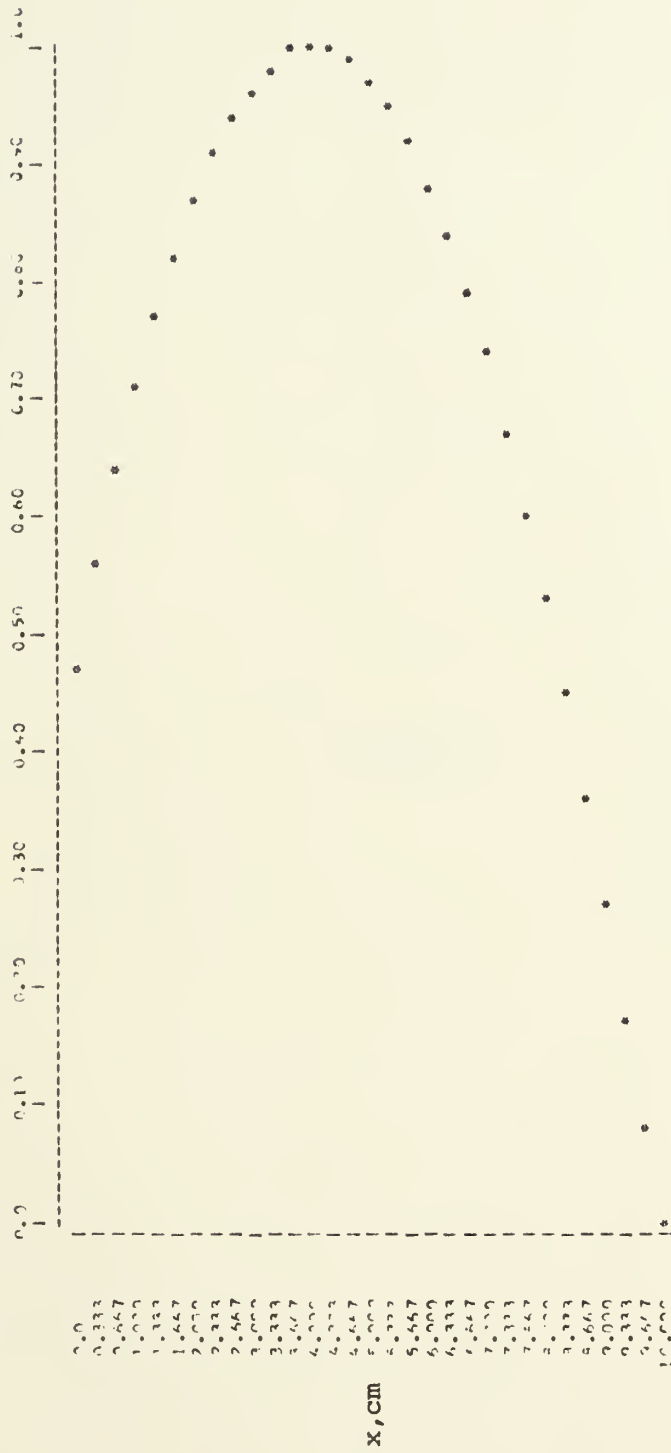








NORMALIZED ANGULAR FLUX VS. SLAB POSITION  
FOR DIRECTION  $\theta_D = -0.9325$





APPENDIX B



## APPENDIX B

Properties of  $||(\mathcal{D}-E)^{-1}S||$

The norm of the transform domain iteration matrix is described by

$$||(\mathcal{D}-E)^{-1}S|| = \frac{\sigma^{\delta}}{2d_i} \left[ 2 \left( \frac{1-\gamma^R}{1-\gamma} \right) - \gamma^{R-1} \right] \quad (1)$$

in which

$$0 \leq \gamma = \frac{|e_i|}{d_i} < 1 \quad (2)$$

and

$$e_i = \frac{2(\mu_i)_{min} - \Delta\sigma^t - \Delta\alpha(\mu_i)_{min}}{2\Delta} \quad (3)$$

$$d_i = \frac{2(\mu_i)_{min} + \Delta\sigma^t + \Delta\alpha(\mu_i)_{min}}{2\Delta} \quad (4)$$

and  $R$  is the number of spatial intervals in the mesh.

The fact that  $||(\mathcal{D}-E)^{-1}S||$  is a monotone decreasing function of  $\alpha$  is verified by analysis of three regions of  $\alpha$ ; small  $\alpha$  near zero, at  $\alpha = \alpha^*$ , and for  $\alpha > \alpha^*$  where

$$\alpha^* = \frac{2(\mu_i)_{min} - \Delta\sigma^t}{2(\mu_i)_{min}}. \quad (5)$$



The derivative of  $||(\mathcal{D}-E)^{-1}S||$  with respect to  $\alpha$  is

$$\frac{d||(\mathcal{D}-E)^{-1}S||}{d\alpha} = - \frac{\sigma^s \mu_i}{2d_i^2} \left[ 2 \left( \frac{1-\gamma}{1-\gamma} \right)^R - \gamma^{R-1} \right] +$$

$$\left\{ \begin{array}{l} - \frac{\sigma^s \mu_i^2}{2\Delta d_i^3} \left\{ 2 \left[ \frac{(1-\gamma^R) - R\gamma^{R-1}(1-\gamma)}{(1-\gamma)^2} \right] - (R-1)\gamma^{R-2} \right\} \quad \text{for } 2\mu_i - \Delta\sigma^t - \Delta\alpha\mu_i > 0. \quad (6a) \\ 0 \quad \text{for } 2\mu_i - \Delta\sigma^t - \Delta\alpha\mu_i = 0. \quad (6b) \end{array} \right.$$

The relationships

$$\frac{d(d_i)}{d\alpha} = \frac{\mu_i}{2} \quad (7)$$

$$\frac{d\gamma}{d\alpha} = - \frac{\mu_i^2}{\Delta d_i^2} \quad (8)$$

for  $2\mu_i - \Delta\sigma^t - \Delta\alpha\mu_i > 0$  have been used in the above determinations.

When  $\alpha$  is small and  $2\mu_i - \Delta\sigma^t - \Delta\alpha\mu_i > 0$ ,

$$\gamma = \frac{|e_i|}{d_i} = \frac{2\mu_i - \Delta\sigma^t - \Delta\alpha\mu_i}{2\mu_i + \Delta\sigma^t + \Delta\alpha\mu_i} = 1 - \epsilon \quad (9)$$

where

$$\epsilon = \frac{\Delta \left( \alpha + \frac{\sigma^t}{\mu_i} \right)}{\left( 1 + \frac{\Delta\sigma^t}{2\mu_i} + \frac{\Delta\alpha}{2} \right)} \quad (10)$$





Expanding for small  $\epsilon$ ,

$$\gamma^R = (1-\epsilon)^R \approx 1-R\epsilon \quad (11)$$

and substituting into (6a) produces

$$\frac{d||(\mathcal{D}-E)^{-1}S||}{d\alpha} \approx -\frac{\sigma^\delta \mu_i}{2d_i^2} \left[ (2R-1) + \epsilon(R-1) \right] - \frac{\sigma^\delta \mu_i^2}{2\Delta d_i^3} (R-1) \left[ R(2+\epsilon) - (1+\epsilon) \right] . \quad (12)$$

This quantity is negative for all  $R$ . When  $R$  is large, as in most practical problems,  $||(\mathcal{D}-E)^{-1}S||$  has a large negative slope.

When  $\alpha = \alpha^*$ ,  $2\mu_i - \Delta\sigma^t - \Delta\alpha\mu_i = 0$  and  $e_i = \gamma = 0$ . In this case

$$\frac{d||(\mathcal{D}-E)^{-1}S||}{d\alpha} = -\frac{\sigma^\delta \mu_i}{d_i^2} \quad (13)$$

from (6b). Observe that the slope of  $||(\mathcal{D}-E)^{-1}S||$  is still negative but is much smaller in magnitude than when  $\alpha$  is small near zero.

By definition (5),  $\alpha^*$  is the value of  $\alpha$  when  $e_i = 0$ , that is,

$$\Delta\alpha^*(\mu_i)_{min} + \Delta\sigma^t - 2(\mu_i)_{min} = 0 . \quad (14)$$

So at  $\alpha^*$ ,  $\gamma = 0$  and

$$||(\mathcal{D}-E)^{-1}S|| = \frac{\sigma^\delta}{d_i} = \frac{\Delta\sigma^\delta}{2(\mu_i)_{min}} . \quad (15)$$

For  $\alpha > \alpha^*$ , let

$$\alpha = \alpha^* + \epsilon \quad (16)$$



where  $0 < \epsilon < \infty$ . Then

$$\gamma = \frac{\Delta \epsilon}{4 + \Delta \epsilon} \quad (17)$$

$$\frac{1}{d_{\lambda}} = \frac{2\Delta}{(\mu_{\lambda})_{min}} \left( \frac{1}{4 + \Delta \epsilon} \right) \quad (18)$$

and

$$||(\mathcal{D}-E)^{-1}S|| = \frac{\Delta \sigma^{\delta}}{2(\mu_{\lambda})_{min}} \left\{ 1 - \frac{(\Delta \epsilon)^R + 2(\Delta \epsilon)^{R-1}}{(4 + \Delta \epsilon)^R} \right\}. \quad (19)$$

The derivative of  $||(\mathcal{D}-E)^{-1}S||$  with respect to  $\Delta \epsilon$  is,

$$\frac{d||(\mathcal{D}-E)^{-1}S||}{d(\Delta \epsilon)} = - \frac{2(2R-1)(\Delta \epsilon)^{R-1} + 8(R-1)(\Delta \epsilon)^{R-2}}{(4 + \Delta \epsilon)^{R+1}} \quad (20)$$

which is negative for all  $\epsilon$ ,  $0 < \epsilon < \infty$ .

Equations (12), (13), and (20) reveal that the norm of the transform domain iteration has a negative slope for  $0 < \alpha < \infty$ , consequently it is a monotone decreasing function of  $\alpha$ .

Equation (19) displays that

$$\begin{aligned} \lim_{\alpha \rightarrow \infty} ||(\mathcal{D}-E)^{-1}S|| &= \lim_{\Delta \epsilon \rightarrow \infty} \left\{ \frac{\Delta \sigma^{\delta}}{2(\mu_{\lambda})_{min}} \left[ 1 - \frac{(\Delta \epsilon)^R + 2(\Delta \epsilon)^{R-1}}{(4 + \Delta \epsilon)^R} \right] \right\} \\ &= 0 \end{aligned}$$

since



$$\lim_{\Delta\epsilon \rightarrow \infty} \left[ \frac{(\Delta\epsilon)^R + 2(\Delta\epsilon)^{R-1}}{(4+\Delta\epsilon)^R} \right] = \frac{R!}{R!} = 1$$

by  $R$  applications of l'Hospital's rule.



## APPENDIX C

HALF-RANGE UNMODIFIED  $S_N$  PROGRAM AND SAMPLE OUTPUT









```

0021 J=0-2
0022 SUM=DABS(F11/DI11)
0023 SUM1=1.0
0024 SUM2=0.
0025 DO 45 I=1,J
0026 SUM1=SUM1+SUM
0027 SUM2=SUM2+SUM1
0028 SUM1=SUM1+SUM
0029
0030 NORM=SIGMA2/2.+(2./DI11)*(1.+SUM2)+1./DI11*SUM41
0031 C THIS PART OF PROGRAM CALCULATES THE ALGORITHM CONVERGENCE
0032 C CRITERION WHICH GUARANTEES THAT FRACTIONAL ERROR IS LESS
0033 C THAN EPS1.
0034 EPS=EPS1/11.-EPS11*(1.-VIR4)
0035 DO 50 I=1,M
0036 X(I)=(1-I)*DELTA
0037 C THE FIRST COLLISION SOURCE IS CALCULATED.
0038 DO 90 J=1,3
0039 DO 40 K=1,4
0040 SOURCE(K,J)=DEXP(-SIGMA*(IX(K)+1)*X(I))/(2.*MU(J))
0041 MIDSOR(K,J)=SOURCE(K,J)
0042 DO 85 J=1,3
0043 DO 95 K=1,4
0044 PHIK(K,J)=0.
0045 C THIS PART OF THE PROGRAM STARTS THE INNER ITERATION. NOTE
0046 C THAT THE INITIAL FLUX VECTOR GUESS IS THE ZERO VECTOR.
0047 DO 212 INNER=1,1000
0048 DO 175 J=1,3
0049 DO 180 K=2,4
0050 PHIK(K,J)=F(IJ)/D(J)*PHI(K-1,J)+1./D(J)*MIDSG(K-1,J)
0051 CONTINUE
0052 C THIS LOOP COMPUTES THE NEW SPATIAL MID-POINT FLUXES FROM THE PRESENT
0053 C ITERATE FLUXES.
0054 DO 230 K=1,4
0055 DO 230 J=1,3
0056 MIDPHIK(J)= (.PHI(K+1,J) + PHIK(J))/2.
0057 C CHECK FOR POINTWISE CONVERGENCE IS CONDUCTED.
0058 C NO CONVERGENCE CHECK IS MADE THE FIRST TIME THROUGH.
0059 IF (INNER-EG-1) GO TO 280
0060 C THE NEW CONVERGENCE CRITERION, BASED ON THE MAXIMUM DIFFERENCE
0061 C AND ITERATION MATRIX NORM, IS USED.
0062 C A TABLE SEARCH IS CONDUCTED FOR THE MAXIMUM DIFFERENCE.
0063 SUM=0.
0064 DO 255 K=1,4
0065 DO 255 J=1,3
0066 SUM1=PHI(K,J)-OLDPHI(K,J)
0067 IF (SUM1.GT. SUM) SUM=SUM1
0068 CONTINUE
0069 DO 260 K=2,4
0070 DO 260 J=1,3
0071 CONV=SUM/OLDPHI(K,J)
0072 IF (CONV.GT. EPS) GO TO 280
0073 CONTINUE
0074 GO TO 600
0075 CONTINUE

```



```

0043 C THIS LOOP CALCULATES THE NEW SOURCE.
0044 DO 290 K=1,M
0045 DO 290 J=1,3
0046 SUM1=0.
0047 DO 295 I=1,3
0048 SUM1=SUM1+HEIGHT(I)*MIDPHIK(I)
0049 MIDSORIK(J)=SIGMA*SUM1*SOURCE(K,J)
0050 DO 295 K=1,M
0051 DO 295 J=1,3
0052 CLOPHIK(J)=PHIK(J)
0053 CLOTTIME
0054 DO 600 WRITE(6,610)
0055 1*ALGORITHM RESULTS ARE LISTED BELOW FOR THE FOLLOWING*,
0056 1* PROBLEM PARAMETERS*
0057 WRITE(6,615)
0058 FORMAT('0',15X,'HALF-RANGE CASE 1 PROBLEM4.0')
0059 WRITE(6,620) A,SIGMA,SIGMA,R
0060 FORMAT('0',10X,'SLAB WIDTH=',F4.1,' CM./20X,'TOTAL ',
0061 1*MACROSCOPIC CROSS SECTION=',F5.4,' 1/CM./20X,'SCATTER ',
0062 1*LONG MACROSCOPIC CROSS SECTION=',F6.4,' 1/CM./20X,
0063 1*NUMBER OF SPATIAL MESH INCREMENTS=',I3,' ')
0064 WRITE(6,625) DELTA
0065 FORMAT('0',15X,'SIZE OF EACH SPATIAL MESH INCREMENT=',
0066 1F7.5,' CM./20X,'ANGULAR QUADRATURE SET USED=SIX ',
0067 1*ORDINATE GAUSS./20X,'SOURCE=FIRST COLLISION',
0068 1* WITH UNIT STRENGTH.0')
0069 WRITE(6,630) FPS,INVER,EPSI
0070 FORMAT('0',4X,'THE FRACTIONAL DIFFERENCE CONVERGENCE',
0071 1* BOUND.',F12.5,' WAS MET AFTER ',I5,' ITERATIONS.',
0072 1* THIS IMPLIES ',F5.4,' AT THE FRACTIONAL ITERATION',
0073 1* ERROR IS LESS THAN ',F6.5,' ')
0074 SUM=E(1)/O(1)
0075 SUM1=1./O(1)
0076 WRITE(6,640) NCR,M,SUM,SUM1
0077 FORMAT('0',4X,'THE INFINITY NORM OF THE ITERATION',
0078 1* MATRIX=',F7.5,' BASED ON THE VALUES OF E(1)/O(1)=',
0079 1F7.5,' AND 1/O(1)=',F7.5,' ')
0080 WRITE(6,650)
0081 FORMAT('0',40X,'THE CONVERGED ITERATE ANGULAR FLUXES ',
0082 1* ARE LISTED')
0083 WRITE(6,660)
0084 FORMAT('0',12X,'A,C.',11X,'MU(1)',15X,'MU(2)',
0085 115X,'MU(3)')
0086 DO 465 K=1,M
0087 WRITE(6,670) X(1),PHIK(J),J=1,3)
0088 FORMAT('0',10X,'F7.4,(3X,F12.5))
0089 WRITE(6,680)
0090 FORMAT('0',15X,'NOTE THAT D O1 MEANS TEN TO THE POWER',
0091 1* ONE.0')
0092 WRITE(6,690)
0093 FORMAT('0',10X,'THE PREVIOUS ITERATE BEFORE CONVER',
0094 1* GENCE) ANGULAR FLUXES ARE LISTED')
0095 WRITE(6,700)
0096 FORMAT('0',12X,'A,C.',11X,'MU(1)',15X,'MU(2)',

```



```

C100
C101
C102
C103
C104
C105
C106
C107

115X,'40(31)'
DO 705 K=1,M
705 WRITE(6,710) X(K),CUDPHI(K,J),J=1,3)
710 FORMAT(' ',30X,F7.4,30X,F12.5)
WRITE(6,720)
720 FORMAT('0',5X,'NOTE THAT 0 OR MEANS TEN TO THE POWER',
1,' ONE.')
DO 900 J=1,3
900 CALL PLOT(M,J)
END
```





THE UNMODIFIED DISCRETE COORDINATES ALGORITHM RESULTS ARE LISTED BELOW FOR THE FOLLOWING PROBLEM PARAMETERS

HALF-RANGE CASE 1 PROBLEM.  
SLAB WIDTH=10.0 CM.  
TOTAL MACROSCOPIC CROSS SECTION=1.0000 1/CM.  
SCATTERING MACROSCOPIC CROSS SECTION=0.9999 1/CM.  
NUMBER OF SPATIAL MESH INCREMENTS= 30 .  
SIZE OF EACH SPATIAL MESH INCREMENT=0.3333 CM.  
ANGULAR QUADRATURE SET USED=SIX COORDINATE GAUSS.  
SOURCE=FIRST COLLISION WITH UNIT STRENGTH.

THE FRACTIONAL DIFFERENCE CONVERGENCE RATIO, 0.10000-07, WAS MET AFTER 59 ITERATIONS. THIS IMPLIES THAT THE FRACTIONAL ITERATION ERROR IS LESS THAN 0.0001 .  
THE INFINITY NORM OF THE ITERATION MATRIX=0.89992 BASED ON THE VALUES OF ELL/D(I)=0.17754 AND 1/D(I)=0.82246 .

THE CONVERTED ITERATE ANGULAR FLUXES ARE LISTED

X,CM.	W(1)	W(2)	M(3)
C,0	0.0	0.0	C,0
0.333	0.513740 00	0.411660 00	0.325000 00
0.667	0.582270 00	0.666120 00	0.580210 00
1.000	0.727670 00	0.796890 00	0.742760 00
1.333	0.764140 00	0.862020 00	0.843520 00
1.667	0.797070 00	0.897800 00	0.905170 00
2.000	0.829670 00	0.918690 00	0.942100 00
2.333	0.863470 00	0.932520 00	0.963710 00
2.667	0.877970 00	0.942470 00	0.975600 00
3.000	0.894430 00	0.950310 00	0.981570 00
3.333	0.904670 00	0.955950 00	0.986040 00
3.667	0.907740 00	0.960420 00	0.989200 00
4.000	0.905740 00	0.963980 00	0.993950 00
4.333	0.906370 00	0.966750 00	0.982500 00
4.667	0.970470 00	0.968890 00	0.964710 00
5.000	0.971970 00	0.970520 00	0.950540 00
5.333	0.972970 00	0.971740 00	0.979970 00
5.667	0.973670 00	0.972660 00	0.976570 00
6.000	0.974070 00	0.973330 00	0.977840 00
6.333	0.974570 00	0.973820 00	0.977220 00
6.667	0.974670 00	0.974170 00	0.976720 00
7.000	0.974770 00	0.974410 00	0.976310 00
7.333	0.974770 00	0.974560 00	0.975950 00
7.667	0.974770 00	0.974660 00	0.975720 00
8.000	0.974770 00	0.974720 00	0.975510 00
8.333	0.974770 00	0.974740 00	0.975370 00
8.667	0.974770 00	0.974730 00	0.975250 00
9.000	0.974670 00	0.974710 00	0.975050 00
9.333	0.974630 00	0.974670 00	0.974940 00
9.667	0.974570 00	0.974630 00	0.974830 00
10.000	0.974510 00	0.974580 00	0.974740 00

NOTE THAT 0.01 MEANS TEN TO THE POWER ONE.



## APPENDIX D

### HALF-RANGE TRANSFORM METHOD PROGRAM AND SAMPLE OUTPUT



```

C THIS PROGRAM UTILIZES THE EXPONENTIAL TRANSFORM TO ACCELERATE
C CONVERGENCE OF THE HALF-RANGE CASE I DISCRETE ORDINATES
C ALGORITHM WITH THE FIRST COLLISION SOURCE.
C THE VARIABLES EMPLOYED ARE:
C A=WIDTH OF SLAB IN CM.
C B=INTEGER GIVING THE NUMBER OF SPATIAL SEGMENTS.
C M=NUMBER OF SPACE FLUX POINTS, INCLUDING BOTH BOUNDARIES.
C SIGMA=TOTAL COLLISION CROSS SECTION IN UNITS 1/CM.
C SIGMA5=MACROSCOPIC SCATTERING CROSS SECTION IN UNITS 1/CM.
C WGTG(J)=WEIGHTS OF THE QUADRATURE SET.
C MU(J)=DISCRETE SET OF DIRECTION COSINES OF ANGLE WITH
C RESPECT TO THE X-AXIS.
C PHI(K,J)=DIRECTIONAL FLUX AT SPATIAL POINTS (K) DESCRIBING
C NEUTRONS GOING IN DIRECTION MU(J).
C MINSOR(K,J)=TOTAL SOURCE TERM EVALUATED AT SPATIAL MIDPOINTS
C AND MU(J). COMPOSED OF SCATTERING TERM PLUS
C THE EXTERNAL SOURCE.
C MIDPHI(K,J)=DIRECTIONAL FLUX EVALUATED AT SPATIAL MIDPOINTS
C DETERMINED FROM PRESENT ITERATION OF PHI(K,J)
C AND USED TO CALCULATE NEXT ITERATE SCATTERING
C SOURCE TERM.
C SOURCE(K,J)=EXTERNAL SOURCE AT SPATIAL MIDPOINTS AND MU(J).
C THIS TERM DOES NOT CHANGE WITH EACH ITERATION.
C EPS=A CONVERGENCE CRITERION FOUND FOR FRACTIONAL DIFFERENCES.
C EPS1=UPPER BOUND ON THE FRACTIONAL ERROR.
C XDO=INFINITY NORM OF THE ITERATION MATRIX.
C EIJ=MATRIX ELEMENT OF (I-E) CORRESPONDING TO MU(I).
C MUJ=MATRIX ELEMENT OF (I-E) CORRESPONDING TO MU(J).
C ALPHA=ACCELERATION PARAMETER.
C NIT=NUMBER OF ITERATIONS TO CONVERGENCE OF UNMODIFIED
C DISCRETE ORDINATES ALGORITHM.

      INTEGER R
      REAL R MU(3),MINSOR(30,3),MIDPHI(30,3),NOEM
      DOUBLE PRECISION PHI(31,3),SOURCE(30,3),SIGMA,SIGMA5,
      TWGTG(3),A,DELTA,SUM,SUM1,SUM2,X(31),ULDPHI(31,3),
      LCMV,D(3),E(3),EPS,EPS1,COMP,COMP1,COMP2,ALPHA
      COMMON /STORE/PHI,X,MU
      NIT=59
      EPS1=0.0001
      A=17.0
      q=30
      w=241
      SIGMA=1.0
      SIGMA5=0.6969
      MU(1) = .23862
      MU(2) = .66121
      MU(3) = .93247
      WGTG(1) = .46741
      WGTG(2) = .35376
      WGTG(3) = .17132
      DELTA=6.74
      ALPHA=0.7

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C THIS PART OF PROGRAM CALCULATES THE OPTIMUM ALPHA.

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0020 C THIS PART OF THE PROGRAM CALCULATES THE NORM OF THE
0021 C UNMODIFIED ALGORITHM ITERATION MATRIX FOR LATER COMPARISON.
0022 F(1)=(2.*MU(1)-DELTA*SIGMA)/(2.*DELTA)
0023 D(1)=(2.*MU(1)+DELTA*SIGMA)/(2.*DELTA)
0024 J=P-2
0025 SUM=DARSIE(1)/D(1)
0026 SUM1=1.0
0027 SUM2=0.
0028 DO 25 I=1,J
0029 SUM1=SUM1*SUM
0030 SUM2=SUM2+SUM1
0031 SUM1=SUM1*SUM
0032 NORM=SIGMA/2.*(2./D(1)*(1.+SUM2)+1./D(1)*SUM1)
0033 COMPA=NORM
0034 COMPA1=F(1)/D(1)
0035 COMPA2=1./D(1)
0036 C THIS PART OF PROGRAM CALCULATES THE ALGORITHM COEFFICIENTS.
0037 DO 30 I=1,3
0038 E(I)=(2.*MU(I)-DELTA*SIGMA+DELTA*ALPHA*MU(I))/(2.*DELTA)
0039 D(I)=(2.*MU(I)+DELTA*SIGMA+DELTA*ALPHA*MU(I))/(2.*DELTA)
0040 C THIS PART OF THE PROGRAM COMPUTES THE NORM OF THE ITERATION
0041 C MATRIX. IT DEPENDS UPON MU(1) BEING THE MINIMUM IN THE SET.
0042 J=P-2
0043 SUM=DARSIE(1)/D(1)
0044 SUM1=1.
0045 SUM2=0.
0046 DO 45 I=1,J
0047 SUM1=SUM1*SUM
0048 SUM2=SUM2+SUM1
0049 SUM1=SUM1*SUM
0050 NORM=SIGMA/2.*(2./D(1)*(1.+SUM2)+1./D(1)*SUM1)
0051 C THIS PART OF PROGRAM CALCULATES THE ALGORITHM CONVERGENCE
0052 C CRITERION WHICH GUARANTEES THAT FRACTIONAL ERROR IS LESS
0053 C THAN EPS1.
0054 EPS=EPS1/(1.-EPS1)*(1.-NORM)
0055 DO 50 I=1,M
0056 X(I)=(1.-DELTA
0057 C THE TRANSFORM DOMAIN FIRST COLLISION SOURCE IS CALCULATED.
0058 DO 60 K=1,R
0059 DO 80 J=1,3
0060 SUM=(X(K+1)*X(K))/2.
0061 SOURCE(K,J)=DEXD(-SUM*(ALPHA+SIGMA/MU(J)))
0062 MIDSR(K,J)=SOURCE(K,J)
0063 DO 65 J=1,3
0064 DO 85 K=1,M
0065 PHIK(J)=0.
0066 C THIS PART OF THE PROGRAM STARTS THE INNER ITERATION. NOTE
0067 C THAT THE INITIAL FLUX VECTOR GUESS IS THE ZERO VECTOR.
0068 DO 312 INNER=1,1000
0069 DO 175 J=1,3
0070 PHIK(J)=F(J)/D(J)*PHI(K-1,J)+1./D(J)*MIDSR(K-1,J)
0071 175 CONTINUE
0072 C THIS LOOP COMPUTES THE NEW SPATIAL MID-POINT FLUXES FROM THE PRESENT

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0063 C ITERATE FLUXES.
0064 DO 230 J=1,3
0065   DO 230 K=1,8
0066     230 WIDPHI(K,J) = 1 PHIK(I+1,J) + PHIK(J))/2.
0067 C CHECK FOR POINTWISE CONVERGENCE IS CONDUCTED.
0068 C NO CONVERGENCE CHECK IS MADE THE FIRST TIME THROUGH.
0069 IF (INVER.EC.1) GO TO 280
0070 C THE NEW CONVERGENCE CRITERION, BASED ON THE MAXIMUM DIFFERENCE
0071 C AND ITERATION MATRIX NORM, IS USED.
0072 C A TABLE SEARCH IS CONDUCTED FOR THE MAXIMUM DIFFERENCE.
0073 SUM=0.
0074 DO 255 K=1,4
0075   DO 255 J=1,3
0076     SUM1=PHI(K,J)-OLDPHI(K,J)
0077     IF (SUM1.GT. SUM) SUM=SUM1
0078   CONTINUE
0079 DO 260 K=2,4
0080   DO 260 J=1,3
0081     CONV=SUM/OLDPHI(K,J)
0082     IF (CONV.GT. EPS) GO TO 280
0083   CONTINUE
0084 GO TO 600
0085 280 CONTINUE
0086 C THIS LOOP CALCULATES THE NEW SOURCE.
0087 DO 290 K=1,8
0088   DO 290 J=1,3
0089     SUM1=0.
0090     DO 295 I=1,3
0091       SUM1=SUM1+WEIGHT(I)*PHI(K,I)
0092       WINDOR(K,J)=SIGN(SUM1,SOURCE(K,J))
0093     DO 295 K=1,4
0094       OLDPHI(K,J)=PHI(K,J)
0095     CONTINUE
0096 295 WRITE(6,615)
0097   FORMAT('11.5X, THE TRANSFORM METHOD ',
0098     11 ALGORITHM RESULTS ARE LISTED BELOW FOR THE FOLLOWING',
0099     11 PROBLEM PARAMETERS')
0100   WRITE(6,615)
0101   FORMAT('101.19X, HALF-RANGE CASE 1 PROBLEM,')
0102   WRITE(6,620) A,SIGMA,SIGMA,R
0103   FORMAT('11.19X, SLAB WIDTH=1.0 CM, 1/20X, TOTAL ',
0104     11 MACROSCOPIC CROSS SECTION=1.66, 1/20X, SCATTER1,
0105     11 MACROSCOPIC CROSS SECT (DN=1.66, 1/20X,
0106     11 NUMBER OF SPATIAL MESH INCREMENTS=13, ')
0107   WRITE(6,625) DELTA
0108   FORMAT('11.19X, SIZE OF EACH SPATIAL MESH INCREMENT=1.
0109     11 1.675, 1 CM, 1/20X, ANGULAR QUADRATURE SET USED=SIX ',
0110     11 WITH UNIT STRENGTH,')
0111   WRITE(6,626) CMPL,CMP2,CMP3
0112   FORMAT('11.19X, UNMODIFIED ALGORITHM COEFFICIENT F11/201,
0113     11 F11=1.66, 1/20X, UNMODIFIED ALGORITHM COEFFICIENT 1/1,
0114     11 D(1)=1.675, 1/20X, UNMODIFIED ALGORITHM ITERATION MAT,
0115     11 PIX NORM=1.675, ')

```







THE TRANSFORM METHOD ALGORITHM RESULTS ARE LISTED BELOW FOR THE FOLLOWING PROBLEM PARAMETERS

HALF-RANGE CASE 1 PROBLEM.  
SLAB WIDTH=10.0 CM.  
TOTAL MACROSCOPIC CROSS SECTION=1.0000 1/CM.  
SCATTERING MACROSCOPIC CROSS SECTION=0.9999 1/CM.  
NUMBER OF SPATIAL MESH ELEMENTS= 30 .  
SIZE OF EACH SPATIAL MESH ELEMENT=0.3333 CM.  
ANGULAR QUADRATURE SET USED=SIX COORDINATE GAUSS.  
SOURCE=FIRST COLLISION WITH INIT STRENGTH.  
UNMODIFIED ALGORITHM COEFFICIENT E(1)/D(1)= 0.17754 .  
UNMODIFIED ALGORITHM COEFFICIENT I/D(1)=0.82246 .  
UNMODIFIED ALGORITHM ITERATION MATRIX NORM=0.99490 .  
NUMBER OF ITERATIONS TO CONVERGENCE OF UNMODIFIED ALGORITHM= 59 .  
ACCELERATION PARAMETER=0.20000 .

THE FRACTIONAL DIFFERENCE CONVERGENCE STAND. 0.456500-05, WAS MET AFTER 48 ITERATIONS. THIS IMPLIES THAT THE FRACTIONAL ITERATION ERROR IS LESS THAN 0.0001 .

THE INFINITY NORM OF THE TRANSFORM DOMAIN ITERATION MATRIX=0.93435 BASED ON THE VALUES OF ALPHA= 0.2000.  
E(1)/D(1)=0.15487 AND I/D(1)=0.82663 .

THE CONVERGED ITERATE SOLUTION ANGULAR FLUXES ARE LISTED			
X,CG.	X,CI	X,CI2	X,CI3
0.0	0.0	0.0	0.0
0.3333	0.612420 00	0.411490 00	0.327400 00
0.6667	0.581600 00	0.667100 00	0.580400 00
1.0000	0.726920 00	0.747650 00	0.743410 00
1.3333	0.784830 00	0.863110 00	0.844210 00
1.6667	0.843700 00	0.898110 00	0.905780 00
2.0000	0.879140 00	0.918940 00	0.942740 00
2.3333	0.909440 00	0.932770 00	0.964220 00
2.6667	0.930450 00	0.942740 00	0.976050 00
3.0000	0.944770 00	0.950300 00	0.981910 00
3.3333	0.954420 00	0.958150 00	0.984310 00
3.6667	0.961120 00	0.968720 00	0.989820 00
4.0000	0.965610 00	0.964290 00	0.984210 00
4.3333	0.968670 00	0.967040 00	0.983140 00
4.6667	0.970740 00	0.969160 00	0.981910 00
5.0000	0.972190 00	0.970760 00	0.980730 00
5.3333	0.973150 00	0.971970 00	0.979600 00
5.6667	0.973820 00	0.972860 00	0.978700 00
6.0000	0.974250 00	0.973500 00	0.977970 00
6.3333	0.974630 00	0.973970 00	0.977330 00
6.6667	0.974720 00	0.974290 00	0.976810 00
7.0000	0.974750 00	0.974500 00	0.976380 00
7.3333	0.974830 00	0.974630 00	0.976040 00
7.6667	0.974830 00	0.974700 00	0.975750 00
8.0000	0.974870 00	0.974730 00	0.975510 00
8.3333	0.974750 00	0.974730 00	0.975310 00
8.6667	0.974630 00	0.974700 00	0.975110 00
9.0000	0.974620 00	0.974650 00	0.974950 00
9.3333	0.974550 00	0.974590 00	0.974800 00
9.6667	0.974450 00	0.974520 00	0.974720 00
10.0000	0.974330 00	0.974440 00	0.974600 00

NOTE THAT 0.01 MEANS TEN TO THE POWER ONE.



THE TRANSFORM DOMAIN PREVIOUS ITERATE ANGULAR FLUXES ARE LISTED

K.C.M.	M(1)	M(2)	M(3)
0.0	0.0	0.0	0.0
0.333	0.51390 00	0.38490 00	0.30630 00
0.667	0.59670 00	0.58380 00	0.50800 00
1.000	0.59510 00	0.65360 00	0.60860 00
1.333	0.60050 00	0.65100 00	0.64660 00
1.667	0.59490 00	0.64330 00	0.64920 00
2.000	0.58930 00	0.61990 00	0.63140 00
2.333	0.57030 00	0.58490 00	0.60460 00
2.667	0.54590 00	0.55300 00	0.57260 00
3.000	0.51510 00	0.52150 00	0.53890 00
3.333	0.49070 00	0.49090 00	0.50540 00
3.667	0.46160 00	0.46140 00	0.47300 00
4.000	0.43380 00	0.43380 00	0.44230 00
4.333	0.40710 00	0.40650 00	0.41360 00
4.667	0.38170 00	0.38110 00	0.38610 00
5.000	0.35760 00	0.35710 00	0.36070 00
5.333	0.33420 00	0.33450 00	0.33710 00
5.667	0.31350 00	0.31320 00	0.31510 00
6.000	0.29340 00	0.29320 00	0.29450 00
6.333	0.27490 00	0.27440 00	0.27530 00
6.667	0.25690 00	0.25680 00	0.25740 00
7.000	0.24030 00	0.24030 00	0.24070 00
7.333	0.22440 00	0.22480 00	0.22510 00
7.667	0.21030 00	0.21030 00	0.21050 00
8.000	0.19680 00	0.19680 00	0.19650 00
8.333	0.18410 00	0.18410 00	0.18420 00
8.667	0.17220 00	0.17220 00	0.17230 00
9.000	0.16100 00	0.16110 00	0.16160 00
9.333	0.15070 00	0.15070 00	0.15070 00
9.667	0.14070 00	0.14090 00	0.14100 00
10.000	0.13180 00	0.13180 00	0.13190 00

NOTE THAT 0.01 MEANS TEN TO THE POWER ONE.





THE TRANSFORM METHOD ALGORITHM RESULTS ARE LISTED BELOW FOR THE FOLLOWING PROBLEM PARAMETERS

WAVE-LENGTH CASE 1 PROBLEM.  
SLAB WIDTH=10.0 CM.  
TOTAL MACROSCOPIC CROSS SECTION=1.0000 1/CM.  
SCATTERING MACROSCOPIC CROSS SECTION=0.9999 1/CM.  
NUMBER OF SPATIAL MESH INCREMENTS= 30 .  
SIZE OF EACH SPATIAL MESH INCREMENT=0.3333 CM.  
ANGULAR QUADRATURE SET USED=SIN COSINATE GAUSS.  
SOURCE=FIRST COLLISION WITH UNIT STRENGTH.  
UNMODIFIED ALGORITHM COEFFICIENT  $\epsilon(1)/\epsilon(11)=0.17754$  .  
UNMODIFIED ALGORITHM COEFFICIENT  $1/\nu(11)=0.82746$  .  
UNMODIFIED ALGORITHM ITERATION MATRIX NORM=0.9990 .  
NUMBER OF ITERATIONS TO CONVERGENCE OF UNMODIFIED ALGORITHM= 59 .  
ACCELERATION PARAMETER=1.80924 .

THE FRACTIONAL DIFFERENCE CONVERGENCE BOUND, 0.30140E-04, WAS MET AFTER 45 ITERATIONS. THIS IMPLIES THAT THE FRACTIONAL ITERATION ERROR IS LESS THAN 0.0001 .

THE INFINITY NORM OF THE TRANSFORM DOMAIN ITERATION MATRIX=0.69839 BASED ON THE VALUES OF ALPHA= 1.8092,  $\epsilon(1)/\nu(11)=0.00000$  AND  $1/\nu(11)=0.69846$  .

THE CONVERGED ITERATE SOLUTION ANGULAR FLUXES ARE LISTED

X, CM.	$\psi(11)$	$\psi(12)$	$\psi(13)$
0.0	0.0	0.0	0.0
0.3333	0.64920 00	0.42430 00	0.335140 00
0.6667	0.67500 00	0.68930 00	0.60030 00
1.0000	0.72350 00	0.83580 00	0.75800 00
1.3333	0.77570 00	0.85700 00	0.845940 00
1.6667	0.82150 00	0.87630 00	0.89160 00
2.0000	0.84940 00	0.89200 00	0.911440 00
2.3333	0.86340 00	0.89830 00	0.915320 00
2.6667	0.86710 00	0.87540 00	0.909530 00
3.0000	0.86410 00	0.86720 00	0.898080 00
3.3333	0.85670 00	0.85710 00	0.88340 00
3.6667	0.84560 00	0.84580 00	0.86720 00
4.0000	0.83450 00	0.83340 00	0.85040 00
4.3333	0.82140 00	0.81950 00	0.83340 00
4.6667	0.8076 00	0.80300 00	0.81670 00
5.0000	0.79340 00	0.79210 00	0.80020 00
5.3333	0.77910 00	0.77490 00	0.78420 00
5.6667	0.76480 00	0.76480 00	0.76810 00
6.0000	0.75060 00	0.75010 00	0.75330 00
6.3333	0.73650 00	0.73640 00	0.73850 00
6.6667	0.72250 00	0.72210 00	0.72400 00
7.0000	0.70860 00	0.70860 00	0.70950 00
7.3333	0.69450 00	0.69450 00	0.69610 00
7.6667	0.68010 00	0.68190 00	0.68260 00
8.0000	0.66890 00	0.66890 00	0.66940 00
8.3333	0.65610 00	0.65610 00	0.65640 00
8.6667	0.64350 00	0.64350 00	0.64380 00
9.0000	0.63110 00	0.63110 00	0.63130 00
9.3333	0.61900 00	0.61900 00	0.61920 00
9.6667	0.60710 00	0.60710 00	0.60720 00
10.0000	0.59540 00	0.59550 00	0.59550 00

NOTE THAT 0.01 MEANS TEN TO THE POWER ONE.



THE TRANSFORM DURING PREVIOUS ITERATE ANGULAR FLUXES ARE LISTED			
X(CM.)	W(1)	W(2)	W(3)
0.0	0.0	0.0	0.0
0.333	0.355210-00	0.242190-00	0.181360-00
0.667	0.200960-00	0.206500-00	0.174700-00
1.0000	0.118010-00	0.132350-00	0.124140-00
1.3333	0.595000-01	0.707990-01	0.755030-01
1.6667	0.407600-01	0.429630-01	0.437140-01
2.0000	0.227450-01	0.236610-01	0.244350-01
2.3333	0.125700-01	0.129270-01	0.134330-01
2.6667	0.698260-02	0.702920-02	0.730310-02
3.0000	0.375400-02	0.340390-02	0.334540-02
3.3333	0.255030-02	0.206020-02	0.212350-02
3.6667	0.111330-02	0.111210-02	0.114050-02
4.0000	0.507490-03	0.599450-03	0.611500-03
4.3333	0.323360-03	0.322780-03	0.328110-03
4.6667	0.171950-03	0.173560-03	0.175910-03
5.0000	0.531050-04	0.533730-04	0.543350-04
5.3333	0.502370-04	0.501790-04	0.505620-04
5.6667	0.263310-04	0.269560-04	0.271130-04
6.0000	0.144870-04	0.144770-04	0.145400-04
6.3333	0.777710-05	0.777320-05	0.779860-05
6.6667	0.417650-05	0.417300-05	0.418320-05
7.0000	0.226260-05	0.224000-05	0.224410-05
7.3333	0.127250-05	0.120230-05	0.120390-05
7.6667	0.545320-06	0.545260-06	0.545910-06
8.0000	0.346310-06	0.346290-06	0.346550-06
8.3333	0.185640-06	0.185640-06	0.185940-06
8.6667	0.997250-07	0.997270-07	0.997730-07
9.0000	0.535140-07	0.535160-07	0.535340-07
9.3333	0.281160-07	0.281180-07	0.287250-07
9.6667	0.150900-07	0.154100-07	0.154130-07
10.0000	0.820640-08	0.826910-08	0.827050-08

NOTE THAT 0.01 MEANS TEN TO THE POWER ONE.



APPENDIX E

DISCRETIZATION ERROR IMPROVEMENT PROGRAM AND SAMPLE OUTPUT









```

1011 IF (NMAX .EQ. 3) G=400
1012 M=0+1
1013 SIGMA=1.0
1014 SIGMA=0.2
1015 W(1) = .20047
1016 W(2) = .44021
1017 W(3) = .33047
1018 W(4) = -.23062
1019 W(5) = -.21121
1020 W(6) = -.03007
1021 W(7) = .46091
1022 W(8) = .16076
1023 W(9) = .11032
1024 W(10) = .44791
1025 W(11) = .36074
1026 W(12) = .11132
1027 DELTA=2.0
1028 DO 50 I=1,M
1029   V(I)=1-10*DELTA
1030   IF (NMAX .EQ. 1) ALPHA=0.
1031   IF (NMAX .EQ. 1) ALPHA=0.
1032   C THIS PART OF PROGRAM CALCULATES THE ALGORITHM COEFFICIENTS.
1033   DO 30 J=1,3
1034     F(J)=(2.*W(J)-DELTA*(SIGMA+DELTA*ALPHA*W(J)))/(2.*DELTA)
1035     G(J)=(2.*W(J)+DELTA*(SIGMA-DELTA*ALPHA*W(J)))/(2.*DELTA)
1036     SUM=0+0+0
1037     DO 30 J=4,6
1038       F(J)=(2.*W(J)-DELTA*(SIGMA-DELTA*ALPHA*SUM))/(2.*DELTA)
1039       G(J)=(2.*W(J)+DELTA*(SIGMA+DELTA*ALPHA*SUM))/(2.*DELTA)
1040   IF (NMAX .EQ. 3) GO TO 700
1041   C THERE IS NO SOURCE TRANSFORMATION FOR THIS PROBLEM.
1042   DO 30 J=1,6
1043     S=0+0+0
1044     DO 30 K=1,2
1045       COEFF(K,J)=0.
1046       W(COEF(K,J))=0.
1047   DO 30 J=1,6
1048     DO 30 K=1,M
1049       W(K,J)=0.
1050   C THIS CASE BE THE PROGRAM STARTS THE INNER ITERATION. NOTE
1051   C THAT THE INITIAL FLUX VECTOR GUESS IS THE ZERO VECTOR.
1052   C THE BOUNDARY CONDITIONS ARE SET.
1053   DO 30 J=1,3
1054     W(1,J)=1.0
1055     DO 30 K=0,1,2,3
1056       W(K,J)=0.
1057   DO 150 K=2,5
1058     W(K,J)=F(J)/G(J)+W(K-1,J)+1./D(J)*W(DSOR(K-1,J)
1059   CONTINUE
1060   CONTINUE
1061   DO 100 J=4,6
1062     DO 100 K=1,5
1063       W(K,J)=F(J)/G(J)+W(K-1,J)+1./D(J)*W(DSOR(K,J)
1064   CONTINUE
1065   CONTINUE
1066   CONTINUE
1067   CONTINUE
1068   CONTINUE
1069   CONTINUE
1070   CONTINUE

```





















```

1057  FORMAT('1Y,16. A POSITIVE QUANTITY IN COLUMN 7 AND',
1058  '10 NEGATIVE IN COLUMN 8 MEANS THE TRANSFORM PRODUCED A 50%
1059  'SOLUTION IN THE DIRECTION 174X, THE IMPROVED DISCRETIZATION',
1060  '10 ERROR BUT OVERSHOT THE 2600 SOLUTION.')
1061  WRITE(6,000) J,ABS(X1(J))
1062  FORMAT('1Y,16,THE BULK SUM OF ABSOLUTE DIFFERENCES ',
1063  '10 IN 2600 SOLUTION AND 2600 SOLUTION FOR MU(1,1),
1064  '10 IS',E12.5,' %')
1065  WRITE(6,000) J,ABS(X2(J))
1066  FORMAT('1Y,16,THE BULK SUM OF ABSOLUTE DIFFERENCES',
1067  '10 IN 2600 SOLUTION AND TRANSFORM METHOD SOLUTION FOR',
1068  '10 MU(1,1) IS',E12.5,' %')
1069  WRITE(6,000) SUM,SUM1
1070  FORMAT('1Y,16,THE TOTAL BULK SUM OF ABSOLUTE DIFFEREN',
1071  '10S IN 2600 SOLUTION AND 2600 SOLUTION IS',E12.5,
1072  '10 174X,THE TOTAL BULK SUM OF ABSOLUTE DIFFERENCES IN',
1073  '10 2600 AND TRANSFORM METHOD SOLUTIONS IS',E12.5,' %')
1074  CONTINUE
1075  END

```



THE TRANSCENDENT METHOD ALGORITHM RESULTS ARE LISTED BELOW FOR THE FOLLOWING PROBLEM PARAMETERS

SLABWIDTH=10.0 CM.  
TOTAL MACROSCOPIC CROSS SECTION=1.0000 1/CM.  
SCATTERING MACROSCOPIC CROSS SECTION=0.2000 1/CM.  
NUMBER OF SPATIAL MESH INCREMENTS= 30 .  
SIZE OF EACH SPATIAL MESH INCREMENT=0.33333 CM.  
ANGULAR QUADRATURE SET USED=SIX ORDINATE GAUSS-LEGENDRE.  
SOURCE=7E40.  
ACCELERATION PARAMETER ALPHA= 0.500 .

THE FRACTIONAL DIFFERENCE CONVERGENCE ROUNDOFF, 0.10000E-03, WAS MET AFTER 10 ITERATIONS.

THE CONVERGED ITERATE ANGULAR FLUXES ARE LISTED									
X,CM.	W(1)	W(2)	W(3)	W(4)	W(5)	W(6)			
0.0	0.10000-01	0.10100-01	0.10000-01	0.69920-01	0.45790-01	0.37750-01			
0.333	0.24210-01	0.63210-00	0.72180-00	0.36230-01	0.24920-01	0.23130-01			
0.667	0.63700-01	0.39600-00	0.51620-00	0.21640-01	0.15230-01	0.12810-01			
1.000	0.15250-01	0.24760-00	0.36700-00	0.13730-01	0.97490-02	0.27590-02			
1.333	0.15760-01	0.15480-00	0.26150-00	0.90100-02	0.64450-02	0.56530-02			
1.667	0.11400-01	0.57150-01	0.18560-00	0.55750-02	0.42340-02	0.36240-02			
2.000	0.73610-02	0.60340-01	0.13160-00	0.39370-02	0.26670-02	0.24300-02			
2.333	0.42410-02	0.38370-01	0.93320-01	0.26750-02	0.19280-02	0.16360-02			
2.667	0.32110-02	0.24220-01	0.64000-01	0.19020-02	0.13020-02	0.11050-02			
3.000	0.1760-02	0.15400-01	0.46720-01	0.12150-02	0.82950-03	0.75040-03			
3.333	0.14640-02	0.97490-02	0.33060-01	0.32360-03	0.60030-03	0.51100-03			
3.667	0.29290-03	0.62170-02	0.23390-01	0.56480-03	0.41040-03	0.34920-03			
4.000	0.47550-03	0.39430-02	0.16520-01	0.35700-03	0.28110-03	0.23940-03			
4.333	0.25120-03	0.25430-02	0.11670-01	0.26510-03	0.19320-03	0.16440-03			
4.667	0.31560-03	0.14510-02	0.82660-02	0.18280-03	0.13330-03	0.11350-03			
5.000	0.21700-03	0.12700-02	0.59220-02	0.12530-03	0.21950-04	0.24360-04			
5.333	0.14050-03	0.63740-03	0.41100-02	0.87010-04	0.63620-04	0.54320-04			
5.667	0.10320-03	0.45640-03	0.29070-02	0.60290-04	0.44120-04	0.37650-04			
6.000	0.71490-04	0.30040-03	0.20460-02	0.41360-04	0.30490-04	0.26030-04			
6.333	0.49570-04	0.19410-03	0.14440-02	0.24110-04	0.21340-04	0.18240-04			
6.667	0.36510-04	0.11510-03	0.10180-02	0.20280-04	0.14480-04	0.12710-04			
7.000	0.30710-04	0.87420-04	0.71950-03	0.16150-04	0.10390-04	0.86940-05			
7.333	0.16710-04	0.54700-04	0.50670-03	0.39970-05	0.72540-05	0.61910-05			
7.667	0.11650-04	0.36430-04	0.35720-03	0.65740-05	0.50330-05	0.41340-05			
8.000	0.21600-05	0.26460-04	0.25190-03	0.43330-05	0.35380-05	0.29750-05			
8.333	0.67000-05	0.19760-04	0.17760-03	0.33410-05	0.24650-05	0.20670-05			
8.667	0.34910-05	0.12390-04	0.12420-03	0.23670-05	0.16370-05	0.14030-05			
9.000	0.27040-05	0.33000-05	0.83240-04	0.16310-05	0.11260-05	0.91000-06			
9.333	0.13630-05	0.57420-05	0.62260-04	0.11360-05	0.69330-06	0.55020-06			
9.667	0.13610-05	0.36430-05	0.43910-04	0.70570-06	0.33820-06	0.25490-06			
10.000	0.33170-06	0.27020-05	0.30300-04	0.0	0.0	0.0			

NOTE THAT 0.01 MEANS 1% TO THE POWER ONE.



THE TRANSCENDENT METHOD ALGORITHM RESULTS ARE LISTED BELOW FOR THE FOLLOWING PROBLEM PARAMETERS

SLABWIDTH=10.0 CM.  
TOTAL MACROSCOPIC CROSS SECTION=1.0000 1/CM.  
SCATTERING MACROSCOPIC CROSS SECTION=0.2000 1/CM.  
NUMBER OF SPATIAL MESH INCREMENTS= 30 .  
SIZE OF EACH SPATIAL MESH INCREMENT=0.3333 CM.  
ANGULAR QUADRATURE SET USED=SIX ORDINATE GAUSS-LEGENDRE.  
SOURCE=7E9.  
ACCELERATION PARAMETER ALPHA= 0.500 .

THE FRACTIONAL DIFFERENCE CONVERGENCE ROUNDOFF, 0.10000E-03, WAS MET AFTER 10 ITERATIONS.

THE CONVERGED ITERATE ANGULAR FLUXES ARE LISTED									
X, CM.	W(11)	W(12)	W(13)	W(14)	W(15)	W(16)			
0.0	0.10000-01	0.10000-01	0.10000-01	0.69942-01	0.45799-01	0.37752-01			
0.333	0.24215-01	0.63210-00	0.72184-00	0.32637-01	0.24492-01	0.22313-01			
0.667	0.37703-01	0.39405-00	0.51625-00	0.21644-01	0.15223-01	0.12814-01			
1.000	0.35512-01	0.24767-00	0.36790-00	0.13735-01	0.97490-02	0.27591-02			
1.333	0.15765-01	0.15489-00	0.26150-00	0.59115-02	0.64465-02	0.56535-02			
1.667	0.11401-01	0.57350-01	0.18567-00	0.55575-02	0.42340-02	0.36246-02			
2.000	0.73412-02	0.60945-01	0.13169-00	0.39375-02	0.26673-02	0.24305-02			
2.333	0.62431-02	0.48370-01	0.93328-01	0.26750-02	0.19281-02	0.19361-02			
2.667	0.32410-02	0.26226-01	0.60900-01	0.18026-02	0.13022-02	0.11058-02			
3.000	0.17620-02	0.15343-01	0.46772-01	0.12113-02	0.62950-03	0.75042-03			
3.333	0.14643-02	0.97497-02	0.33063-01	0.82380-03	0.60330-03	0.51110-03			
3.667	0.20295-03	0.62178-02	0.23395-01	0.56467-03	0.41043-03	0.34923-03			
4.000	0.47553-03	0.39334-02	0.16529-01	0.35670-03	0.28112-03	0.23946-03			
4.333	0.46127-03	0.25837-02	0.11677-01	0.26510-03	0.19322-03	0.16440-03			
4.667	0.31560-03	0.16517-02	0.82469-02	0.18243-03	0.13313-03	0.11350-03			
5.000	0.21707-03	0.12703-02	0.59226-02	0.12533-03	0.21950-04	0.24360-04			
5.333	0.14054-03	0.69749-03	0.41101-02	0.87012-04	0.63662-04	0.54320-04			
5.667	0.10327-03	0.45640-03	0.29037-02	0.60237-04	0.44180-04	0.37656-04			
6.000	0.71492-04	0.30004-03	0.20468-02	0.41345-04	0.30490-04	0.26203-04			
6.333	0.69573-04	0.19419-03	0.14441-02	0.24117-04	0.21340-04	0.18242-04			
6.667	0.36610-04	0.13151-03	0.10187-02	0.20283-04	0.16480-04	0.12715-04			
7.000	0.30970-04	0.17472-04	0.71951-03	0.16163-04	0.10391-04	0.86540-05			
7.333	0.16716-04	0.52702-04	0.50674-03	0.39970-05	0.72564-05	0.61981-05			
7.667	0.11650-04	0.34430-04	0.35760-03	0.60374-05	0.50533-05	0.43140-05			
8.000	0.61050-05	0.26463-04	0.25193-03	0.43331-05	0.35380-05	0.29750-05			
8.333	0.67000-05	0.19376-04	0.17763-03	0.33310-05	0.24565-05	0.20677-05			
8.667	0.34510-05	0.12393-04	0.12528-03	0.21637-05	0.16379-05	0.14032-05			
9.000	0.27024-05	0.93600-05	0.83324-04	0.16533-05	0.11276-05	0.91806-06			
9.333	0.15533-05	0.57427-05	0.62266-04	0.11344-05	0.69933-06	0.55052-06			
9.667	0.13617-05	0.36435-05	0.43991-04	0.70573-06	0.33920-06	0.25497-06			
10.000	0.93370-06	0.27020-05	0.30330-04	0.0	0.0	0.0			

NOTE THAT 0.01 MEANS 1E-01 TO THE POWER ONE.





COMPARISON OF RESULTS FOR THREE DIFFERENT ALGORITHMS ARE MADE FOR MULT1 PART OF SOLUTION

XLOC.	UNMODIFIED R=30 SOLUTION	TRANSFORM METHOD R=30 SOLUTION	UNMODIFIED R=600 SOLUTION	UNMODIFIED DIFFERENCE	TRANSFORM METHOD DIFFERENCE	TRANSFORM METHOD DIFFERENCE
0.0	0.100000-01	0.100000-01	0.100000-01	0.0	0.0	0.0
0.3333	0.242150-00	0.242150-00	0.290100-00	0.579200-01	0.257040-01	0.369560-01
0.6667	0.437330-01	0.437330-01	0.131900-00	0.272720-01	0.915840-02	0.181030-01
1.0000	0.432510-01	0.432510-01	0.419640-01	0.989240-02	0.317590-02	0.671240-02
1.3333	0.176550-01	0.176550-01	0.210210-01	0.337300-02	0.112500-02	0.225000-02
1.6667	0.116410-01	0.116410-01	0.121430-01	0.121790-02	0.475610-03	0.742480-03
2.0000	0.734120-02	0.734120-02	0.537440-02	0.515710-03	0.235750-03	0.257250-03
2.3333	0.444310-02	0.444310-02	0.494520-02	0.269410-03	0.161740-03	0.102120-03
2.6667	0.323130-02	0.323130-02	0.438260-02	0.167190-03	0.117520-03	0.492720-04
3.0000	0.217260-02	0.217260-02	0.219480-02	0.113390-03	0.657420-04	0.283550-04
3.3333	0.146420-02	0.146420-02	0.148320-02	0.198360-04	0.615660-04	0.162700-04
3.6667	0.123350-03	0.123350-03	0.106530-02	0.569460-04	0.445510-04	0.123350-04
4.0000	0.643610-03	0.643610-03	0.654160-03	0.407420-04	0.321700-04	0.857290-05
4.3333	0.437750-03	0.437750-03	0.467240-03	0.291570-04	0.231670-04	0.597330-05
4.6667	0.315720-03	0.315720-03	0.320130-03	0.204720-04	0.166520-04	0.417510-05
5.0000	0.217070-03	0.217070-03	0.215990-03	0.204720-04	0.127090-04	0.292450-05
5.3333	0.165540-03	0.165540-03	0.151440-03	0.136860-04	0.863520-05	0.204790-05
5.6667	0.123270-03	0.123270-03	0.104710-03	0.764930-05	0.621340-05	0.143940-05
6.0000	0.714920-04	0.714920-04	0.724490-04	0.547870-05	0.447130-05	0.100740-05
6.3333	0.435740-04	0.435740-04	0.512870-04	0.332570-05	0.321570-05	0.707590-06
6.6667	0.344510-04	0.344510-04	0.349450-04	0.231550-05	0.231570-05	0.446420-06
7.0000	0.246740-04	0.246740-04	0.263300-04	0.202140-05	0.170730-05	0.331500-06
7.3333	0.147140-04	0.147140-04	0.169620-04	0.145250-05	0.123410-05	0.248340-06
7.6667	0.116450-04	0.116450-04	0.118410-04	0.104420-05	0.305710-06	0.175750-06
8.0000	0.815350-05	0.815350-05	0.827510-05	0.751660-06	0.626440-06	0.124570-06
8.3333	0.620220-05	0.620220-05	0.478450-05	0.540460-06	0.452770-06	0.883370-07
8.6667	0.359910-05	0.359910-05	0.405180-05	0.338760-06	0.326230-06	0.627270-07
9.0000	0.273240-05	0.273240-05	0.223680-05	0.279770-06	0.235360-06	0.444090-07
9.3333	0.194330-05	0.194330-05	0.198440-05	0.200770-06	0.157580-06	0.311100-07
9.6667	0.135170-05	0.135170-05	0.138300-05	0.143210-06	0.122000-06	0.212640-07
10.0000	0.933710-06	0.933710-06	0.949590-06	0.101970-06	0.857130-07	0.158790-07

UNMODIFIED DIFFERENCE=(UNMODIFIED R=30 SOLUTION)-(UNMODIFIED R=600 SOLUTION).

REMARK THAT THIS QUANTITY IS POSITIVE FOR ALL SOLUTION VALUES.

TRANSFORM METHOD DIFFERENCE IS NEXT TO LAST COLUMN=(TRANSFORM METHOD R=30 SOLUTION)-(UNMODIFIED R=30 SOLUTION).

A POSITIVE QUANTITY HERE MEANS THE TRANSFORM RESULT IS IN THE PROPER DIRECTION.

TRANSFORM METHOD DIFFERENCE IN LAST COLUMN=(UNMODIFIED R=600 SOLUTION)-(TRANSFORM METHOD R=30 SOLUTION).

THE KEY TO INTERPRETING THE TABLE IS:

1. THE FIFTH SPATIAL MESH, R=600, PROVIDES LARGER SOLUTION VALUES THAN THE R=30 MESH.
2. A POSITIVE QUANTITY IN COLUMNS 7 AND 8 MEANS THE TRANSFORM METHOD DECREASED THE DISCRETIZATION ERROR.
3. A NEGATIVE QUANTITY IN COLUMN 7 MEANS THE TRANSFORM INCREASED THE DISCRETIZATION ERROR.
4. A POSITIVE QUANTITY IN COLUMN 7 AND NEGATIVE IN COLUMN 8 MEANS THE TRANSFORM PRODUCED A SOLUTION IN THE DIRECTION OF IMPROVED DISCRETIZATION ERROR BUT OVERSHOT THE R=600 SOLUTION.

THE RULK SUM OF ABSOLUTE DIFFERENCES IN R=600 SOLUTION AND R=30 SOLUTION FOR MULT1 IS 0.101030-00.

THE RULK SUM OF ABSOLUTE DIFFERENCES IN R=600 SOLUTION AND TRANSFORM METHOD SOLUTION FOR MULT1 IS 0.652670-01.

THE TOTAL RULK SUM OF ABSOLUTE DIFFERENCES IN R=600 SOLUTION AND R=30 SOLUTION IS 0.173520-00.

THE TOTAL RULK SUM OF ABSOLUTE DIFFERENCES IN R=600 AND TRANSFORM METHOD SOLUTIONS IS 0.813130-01.



COMPARISON OF RESULTS FOR THREE DIFFERENT ALGORITHMS ARE MADE FOR MU(2) PART OF SOLUTION

X-CL.	UNMODIFIED R=30 SOLUTION	TRANSFORM METHOD R=30 SOLUTION	UNMODIFIED R=600 SOLUTION	UNMODIFIED DIFFERENCE	TRANSFORM METHOD DIFFERENCE	TRANSFORM METHOD DIFFERENCE
0.0	0.100000-01	0.100000-01	0.100000-01	0.0	0.0	0.0
0.3333	0.620520-02	0.532710-02	0.532710-02	0.421550-02	0.368790-02	0.527810-03
0.6667	0.391570-02	0.356050-02	0.397690-02	0.845820-02	0.502510-02	0.144310-02
1.0000	0.267400-02	0.247600-02	0.246230-02	0.642710-02	0.480170-02	0.162560-02
1.3333	0.158490-02	0.154890-02	0.156320-02	0.542920-02	0.394950-02	0.143240-02
1.6667	0.093610-02	0.090500-02	0.091450-02	0.423360-02	0.309370-02	0.113490-02
2.0000	0.566100-01	0.605450-01	0.617950-01	0.315420-02	0.230420-02	0.850320-03
2.3333	0.347020-01	0.393700-01	0.338960-01	0.228230-02	0.160610-02	0.616030-03
2.6667	0.217470-01	0.242750-01	0.246620-01	0.161420-02	0.118270-02	0.436460-03
3.0000	0.145150-01	0.165430-01	0.155470-01	0.113190-02	0.087530-02	0.304370-03
3.3333	0.091760-02	0.094670-02	0.090940-02	0.782760-03	0.573010-03	0.205740-03
3.6667	0.597470-02	0.621740-02	0.636100-02	0.536910-03	0.393690-03	0.142220-03
4.0000	0.371170-02	0.398050-02	0.407170-02	0.346010-03	0.268910-03	0.197050-04
4.3333	0.237600-02	0.255870-02	0.262410-02	0.249370-03	0.182910-03	0.654570-04
4.6667	0.157770-02	0.165170-02	0.165860-02	0.157970-03	0.124040-03	0.437300-04
5.0000	0.084020-03	0.107070-02	0.110030-02	0.113350-03	0.839660-04	0.253810-04
5.3333	0.640700-03	0.697490-03	0.717500-03	0.753820-04	0.567830-04	0.149590-04
5.6667	0.410000-03	0.456400-03	0.465440-03	0.516430-04	0.383940-04	0.130500-04
6.0000	0.274000-03	0.300740-03	0.308720-03	0.346520-04	0.259740-04	0.867820-05
6.3333	0.157600-03	0.191300-03	0.203950-03	0.233570-04	0.175910-04	0.576770-05
6.6667	0.110580-03	0.131510-03	0.136350-03	0.157660-04	0.119300-04	0.383310-05
7.0000	0.705670-04	0.376720-04	0.902210-04	0.106610-04	0.811200-05	0.254860-05
7.3333	0.531000-04	0.587040-04	0.604040-04	0.722380-05	0.552770-05	0.169600-05
7.6667	0.357000-04	0.396030-04	0.406130-04	0.690730-05	0.377710-05	0.113020-05
8.0000	0.250760-04	0.266630-04	0.274170-04	0.334290-05	0.256840-05	0.754400-06
8.3333	0.152360-04	0.180740-04	0.185800-04	0.228400-05	0.177930-05	0.504700-06
8.6667	0.110700-04	0.122300-04	0.126370-04	0.156530-05	0.122640-05	0.338300-06
9.0000	0.754730-05	0.839600-05	0.862340-05	0.107610-05	0.848670-06	0.227390-06
9.3333	0.515050-05	0.574320-05	0.590130-05	0.741930-06	0.588780-06	0.153240-06
9.6667	0.353600-05	0.384350-05	0.404650-05	0.512470-06	0.409500-06	0.102990-06
10.0000	0.241240-05	0.272290-05	0.277320-05	0.354740-06	0.284460-06	0.702810-07

THE KEY TO INTERPRETING THE TABLE IS:

1. THE FINE SPATIAL MESH, R=600, PRODUCES LARGER SOLUTION VALUES THAN THE R=30 MESH.
2. A POSITIVE QUANTITY IN COLUMNS 7 AND 8 MEANS THE TRANSFORM METHOD DECREASED THE DISCRETIZATION ERROR.
3. A NEGATIVE QUANTITY IN COLUMN 7 MEANS THE TRANSFORM INCREASED THE DISCRETIZATION ERROR.
4. A POSITIVE QUANTITY IN COLUMN 7 AND NEGATIVE IN COLUMN 8 MEANS THE TRANSFORM PRODUCED A SOLUTION IN THE DIRECTION OF IMPROVED DISCRETIZATION ERROR BUT OVERSHOT THE R=600 SOLUTION.

THE BULK SUM OF ABSOLUTE DIFFERENCES IN R=600 SOLUTION AND R=30 SOLUTION FOR MU(2) IS 0.374110-01.

THE BULK SUM OF ABSOLUTE DIFFERENCES IN R=600 SOLUTION AND TRANSFORM METHOD SOLUTION FOR MU(2) IS 0.901810-02.

THE TOTAL BULK SUM OF ABSOLUTE DIFFERENCES IN R=600 SOLUTION AND R=30 SOLUTION IS 0.173420-01.

THE TOTAL BULK SUM OF ABSOLUTE DIFFERENCES IN R=600 AND TRANSFORM METHOD SOLUTIONS IS 0.813130-01.

UNMODIFIED DIFFERENCE (UNMODIFIED R=600 SOLUTION) - (UNMODIFIED R=30 SOLUTION).

OBSERVE THAT THIS QUANTITY IS POSITIVE FOR ALL SOLUTION VALUES.

TRANSFORM METHOD DIFFERENCE IN NEXT TO LAST COLUMN (TRANSFORM METHOD R=30 SOLUTION) - (UNMODIFIED R=30 SOLUTION).

A POSITIVE QUANTITY HERE MEANS THE TRANSFORM RESULT IS IN THE PROPER DIRECTION.

TRANSFORM METHOD DIFFERENCE IN LAST COLUMN = (UNMODIFIED R=600 SOLUTION) - (TRANSFORM METHOD R=30 SOLUTION).



COMPARISON OF RESULTS FOR THREE DIFFERENT ALGORITHMS ARE MADE FOR MU(3) PART OF SOLUTION

X,CN.	UNMODIFIED R=30 SOLUTION	TRANSFORM METHOD R=30 SOLUTION	UNMODIFIED R=600 SOLUTION	UNMODIFIED DIFFERENCE	TRANSFORM METHOD DIFFERENCE	TRANSFORM METHOD DIFFERENCE
0.0	0.100000-01	0.100000-01	0.100000-01	0.0	0.0	0.0
0.3333	0.700000-00	0.721840-00	0.771420-00	0.122200-02	0.163790-02	-0.415530-03
0.6667	0.518000-00	0.516250-00	0.516290-00	0.777430-02	0.274030-02	0.239970-04
1.0000	0.364700-00	0.367930-00	0.368040-00	0.330050-02	0.303090-02	0.279510-03
1.3333	0.246600-00	0.261500-00	0.261840-00	0.336150-02	0.326450-02	0.326580-03
1.6667	0.132000-00	0.185670-00	0.196030-00	0.303500-02	0.268170-02	0.353830-03
2.0000	0.100000-00	0.131490-00	0.132010-00	0.262370-02	0.230160-02	0.318930-03
2.3333	0.016100-01	0.022200-01	0.036010-01	0.210010-02	0.151930-02	0.273740-03
2.6667	0.646300-01	0.660000-01	0.663180-01	0.175530-02	0.155400-02	0.227500-03
3.0000	0.455000-01	0.467700-01	0.465580-01	0.143100-02	0.124560-02	0.135470-03
3.3333	0.310100-01	0.330930-01	0.332310-01	0.113060-02	0.092120-02	0.146510-03
3.6667	0.200000-01	0.223300-01	0.235070-01	0.083110-02	0.065770-02	0.117330-03
4.0000	0.150300-01	0.165290-01	0.166210-01	0.063260-02	0.059170-02	0.091630-03
4.3333	0.112240-01	0.116770-01	0.117490-01	0.524420-03	0.453440-03	0.709590-04
4.6667	0.700150-02	0.826630-02	0.830130-02	0.393730-03	0.365250-03	0.545350-04
5.0000	0.556130-02	0.592260-02	0.596430-02	0.302930-03	0.261370-03	0.416140-04
5.3333	0.391320-02	0.411010-02	0.414170-02	0.222450-03	0.196950-03	0.315490-04
5.6667	0.275300-02	0.290070-02	0.292450-02	0.171490-03	0.147660-03	0.226280-04
6.0000	0.194500-02	0.206430-02	0.206470-02	0.128320-03	0.110310-03	0.179040-04
6.3333	0.136100-02	0.144410-02	0.145750-02	0.095300-04	0.082130-04	0.133540-04
6.6667	0.077710-03	0.101470-02	0.102370-02	0.709530-04	0.609600-04	0.559300-05
7.0000	0.673300-03	0.711450-03	0.725940-03	0.525510-04	0.455120-04	0.742510-05
7.3333	0.473400-03	0.506740-03	0.512250-03	0.339220-04	0.333150-04	0.550730-05
7.6667	0.312000-03	0.357360-03	0.361430-03	0.286140-04	0.265470-04	0.407220-05
8.0000	0.236650-03	0.251000-03	0.256000-03	0.210450-04	0.186420-04	0.300410-05
8.3333	0.184650-03	0.177680-03	0.170690-03	0.154500-04	0.132330-04	0.221150-05
8.6667	0.115650-03	0.125240-03	0.125920-03	0.113220-04	0.096770-04	0.162430-05
9.0000	0.310000-04	0.408340-04	0.895150-04	0.328320-05	0.709160-05	0.119160-05
9.3333	0.570470-04	0.622660-04	0.631330-04	0.675090-05	0.517950-05	0.872290-06
9.6667	0.411150-04	0.433800-04	0.445240-04	0.441350-05	0.377620-05	0.637370-06
10.0000	0.291910-04	0.300930-04	0.313540-04	0.321490-05	0.274920-05	0.465700-06

UNMODIFIED DIFFERENCE=UNMODIFIED R=600 SOLUTION-UNMODIFIED R=30 SOLUTION.

NOTE THAT THIS QUANTITY IS POSITIVE FOR ALL SOLUTION VALUES.

TRANSFORM METHOD DIFFERENCE IN NEXT TO LAST COLUMN=TRANSFORM METHOD R=30 SOLUTION-UNMODIFIED R=30 SOLUTION.

A POSITIVE QUANTITY HERE MEANS THE TRANSFORM RESULT IS IN THE PROPER DIRECTION.

TRANSFORM METHOD DIFFERENCE IN LAST COLUMN=(UNMODIFIED R=600 SOLUTION)-(TRANSFORM METHOD R=30 SOLUTION).

THE KEY TO INTERPRETING THE TABLE IS:

1. THE FINED SPATIAL MESH, R=600, PRODUCES LARGER SOLUTION VALUES THAN THE R=30 MESH.
2. A POSITIVE QUANTITY IN COLUMNS 7 AND 8 MEANS THE TRANSFORM METHOD DECREASED THE DISCRETIZATION ERROR.
3. A NEGATIVE QUANTITY IN COLUMN 7 MEANS THE TRANSFORM INCREASED THE DISCRETIZATION ERROR.
4. A POSITIVE QUANTITY IN COLUMN 8 AND NEGATIVE IN COLUMN 9 MEANS THE TRANSFORM PRODUCED A SOLUTION IN THE DIRECTION OF IMPROVED DISCRETIZATION ERROR BUT OVERSHOT THE R=600 SOLUTION.

THE RISK SUM OF ABSOLUTE DIFFERENCES IN R=600 SOLUTION AND R=30 SOLUTION FOR MU(3) IS 0.265690-01.

THE RISK SUM OF ABSOLUTE DIFFERENCES IN R=600 SOLUTION AND TRANSFORM METHOD SOLUTION FOR MU(3) IS 0.309470-02.

THE TOTAL RISK SUM OF ABSOLUTE DIFFERENCES IN R=600 SOLUTION AND R=30 SOLUTION IS 0.173520-00.

THE TOTAL RISK SUM OF ABSOLUTE DIFFERENCES IN R=600 AND TRANSFORM METHOD SOLUTION IS 0.813130-01.



COMPARISON OF RESULTS FOR THREE DIFFERENT ALGORITHMS ARE MADE FOR MU(4) PART OF SOLUTION

X.CO.	UNMODIFIED		TRANSFORM METHOD R=600 SOLUTION		UNMODIFIED		TRANSFORM METHOD R=30 SOLUTION		TRANSFORM METHOD R=30 SOLUTION	
	DIFFERENCE	DIFFERENCE	DIFFERENCE	DIFFERENCE	DIFFERENCE	DIFFERENCE	DIFFERENCE	DIFFERENCE	DIFFERENCE	DIFFERENCE
0.0	0.49420-01	0.699620-01	0.31810-01	0.160770-02	-0.732610-13	0.423830-13	0.11354-12	0.94431-03	0.52355-03	0.22125-03
0.1333	0.355740-01	0.562770-01	0.2216440-01	0.124570-01	0.490520-03	0.21510-03	0.52355-03	0.22125-03	0.191430-03	0.144070-03
0.26667	0.217230-01	0.371970-01	0.124570-01	0.124570-01	0.490520-03	0.21510-03	0.52355-03	0.22125-03	0.191430-03	0.144070-03
1.0000	0.135770-01	0.217230-01	0.124570-01	0.124570-01	0.490520-03	0.21510-03	0.52355-03	0.22125-03	0.191430-03	0.144070-03
1.3333	0.492240-02	0.597560-02	0.355740-02	0.355740-02	0.490520-03	0.21510-03	0.52355-03	0.22125-03	0.191430-03	0.144070-03
1.6667	0.317970-02	0.492240-02	0.355740-02	0.355740-02	0.490520-03	0.21510-03	0.52355-03	0.22125-03	0.191430-03	0.144070-03
2.0000	0.259260-02	0.317970-02	0.355740-02	0.355740-02	0.490520-03	0.21510-03	0.52355-03	0.22125-03	0.191430-03	0.144070-03
2.3333	0.174110-02	0.259260-02	0.355740-02	0.355740-02	0.490520-03	0.21510-03	0.52355-03	0.22125-03	0.191430-03	0.144070-03
2.6667	0.117430-02	0.174110-02	0.355740-02	0.355740-02	0.490520-03	0.21510-03	0.52355-03	0.22125-03	0.191430-03	0.144070-03
3.0000	0.705270-03	0.117430-02	0.355740-02	0.355740-02	0.490520-03	0.21510-03	0.52355-03	0.22125-03	0.191430-03	0.144070-03
3.3333	0.564870-03	0.705270-03	0.355740-02	0.355740-02	0.490520-03	0.21510-03	0.52355-03	0.22125-03	0.191430-03	0.144070-03
3.6667	0.360530-03	0.564870-03	0.355740-02	0.355740-02	0.490520-03	0.21510-03	0.52355-03	0.22125-03	0.191430-03	0.144070-03
4.0000	0.25210-03	0.360530-03	0.355740-02	0.355740-02	0.490520-03	0.21510-03	0.52355-03	0.22125-03	0.191430-03	0.144070-03
4.3333	0.173070-03	0.25210-03	0.355740-02	0.355740-02	0.490520-03	0.21510-03	0.52355-03	0.22125-03	0.191430-03	0.144070-03
4.6667	0.110770-03	0.173070-03	0.355740-02	0.355740-02	0.490520-03	0.21510-03	0.52355-03	0.22125-03	0.191430-03	0.144070-03
5.0000	0.421100-04	0.110770-03	0.355740-02	0.355740-02	0.490520-03	0.21510-03	0.52355-03	0.22125-03	0.191430-03	0.144070-03
5.3333	0.563750-04	0.421100-04	0.355740-02	0.355740-02	0.490520-03	0.21510-03	0.52355-03	0.22125-03	0.191430-03	0.144070-03
5.6667	0.393040-04	0.563750-04	0.355740-02	0.355740-02	0.490520-03	0.21510-03	0.52355-03	0.22125-03	0.191430-03	0.144070-03
6.0000	0.272550-04	0.393040-04	0.355740-02	0.355740-02	0.490520-03	0.21510-03	0.52355-03	0.22125-03	0.191430-03	0.144070-03
6.3333	0.190430-04	0.272550-04	0.355740-02	0.355740-02	0.490520-03	0.21510-03	0.52355-03	0.22125-03	0.191430-03	0.144070-03
6.6667	0.131700-04	0.190430-04	0.355740-02	0.355740-02	0.490520-03	0.21510-03	0.52355-03	0.22125-03	0.191430-03	0.144070-03
7.0000	0.917930-05	0.131700-04	0.355740-02	0.355740-02	0.490520-03	0.21510-03	0.52355-03	0.22125-03	0.191430-03	0.144070-03
7.3333	0.640210-05	0.917930-05	0.355740-02	0.355740-02	0.490520-03	0.21510-03	0.52355-03	0.22125-03	0.191430-03	0.144070-03
7.6667	0.445570-05	0.640210-05	0.355740-02	0.355740-02	0.490520-03	0.21510-03	0.52355-03	0.22125-03	0.191430-03	0.144070-03
8.0000	0.311740-05	0.445570-05	0.355740-02	0.355740-02	0.490520-03	0.21510-03	0.52355-03	0.22125-03	0.191430-03	0.144070-03
8.3333	0.217540-05	0.311740-05	0.355740-02	0.355740-02	0.490520-03	0.21510-03	0.52355-03	0.22125-03	0.191430-03	0.144070-03
8.6667	0.151340-05	0.217540-05	0.355740-02	0.355740-02	0.490520-03	0.21510-03	0.52355-03	0.22125-03	0.191430-03	0.144070-03
9.0000	0.103460-05	0.151340-05	0.355740-02	0.355740-02	0.490520-03	0.21510-03	0.52355-03	0.22125-03	0.191430-03	0.144070-03
9.3333	0.627900-05	0.103460-05	0.355740-02	0.355740-02	0.490520-03	0.21510-03	0.52355-03	0.22125-03	0.191430-03	0.144070-03
9.6667	0.0	0.627900-05	0.355740-02	0.355740-02	0.490520-03	0.21510-03	0.52355-03	0.22125-03	0.191430-03	0.144070-03
10.0000	0.0	0.0	0.355740-02	0.355740-02	0.490520-03	0.21510-03	0.52355-03	0.22125-03	0.191430-03	0.144070-03

UNMODIFIED DIFFERENCE=UNMODIFIED R=600 SOLUTION-(UNMODIFIED R=30 SOLUTION).

MEANS THAT THIS QUANTITY IS POSITIVE FOR ALL SOLUTION VALUES.

TRANSFORM METHOD DIFFERENCE IN NEXT TO LAST COLUMN=TRANSFORM METHOD R=600 SOLUTION-(UNMODIFIED R=30 SOLUTION).

A POSITIVE QUANTITY MEANS THE TRANSFORM RESULT IS IN THE PROPER DIRECTION.

TRANSFORM METHOD DIFFERENCE IN LAST COLUMN=UNMODIFIED R=600 SOLUTION-(TRANSFORM METHOD R=30 SOLUTION).

THE KEY TO INTERPRETING THE TABLE IS:

1. THE FINER SPATIAL MESH, R=600, PRODUCES LARGER SOLUTION VALUES THAN THE R=30 MESH.
2. A POSITIVE QUANTITY IN COLUMNS 7 AND 8 MEANS THE TRANSFORM METHOD DECREASED THE DISCRETIZATION ERROR.
3. A NEGATIVE QUANTITY IN COLUMNS 7 AND 8 MEANS THE TRANSFORM INCREASED THE DISCRETIZATION ERROR.
4. A POSITIVE QUANTITY IN COLUMN 7 AND NEGATIVE IN COLUMN 8 MEANS THE TRANSFORM PRODUCED A SOLUTION IN THE DIRECTION OF IMPROVED DISCRETIZATION ERROR BUT OVERSHOT THE R=600 SOLUTION.

THE RULK SUM OF ABSOLUTE DIFFERENCES IN R=600 SOLUTION AND R=30 SOLUTION FOR MU(4) IS 0.460690-02 .

THE RULK SUM OF ABSOLUTE DIFFERENCES IN R=600 SOLUTION AND TRANSFORM METHOD SOLUTION FOR MU(4) IS 0.195070-02 .

THE TOTAL RULK SUM OF ABSOLUTE DIFFERENCES IN R=600 SOLUTION AND R=30 SOLUTION IS 0.173520 CC .

THE TOTAL RULK SUM OF ABSOLUTE DIFFERENCES IN R=600 AND TRANSFORM METHOD SOLUTIONS IS 0.813130-01 .









COMPARISON OF RESULTS FOR THREE DIFFERENT ALGORITHMS ARE MADE FOR MU(6) PART OF SOLUTION

X.C.C.	UNMODIFIED P=600 SOLUTION	TRANSFORM METHOD P=600 SOLUTION	UNMODIFIED P=600 SOLUTION	UNMODIFIED DIFFERENCE	TRANSFORM METHOD DIFFERENCE	TRANSFORM METHOD DIFFERENCE
0.0	0.377500-01	0.377500-01	-0.235310-11	0.136190-11	-0.371500-11	-0.371500-11
0.1333	0.265100-01	0.260910-01	0.212120-01	0.302100-03	0.325925-03	0.325925-03
0.2667	0.124640-01	0.129160-01	0.130340-01	0.429680-03	0.211230-03	0.211230-03
1.0000	0.012590-02	0.012750-02	0.012520-02	0.249230-03	0.145950-03	0.145950-03
1.3333	0.534370-02	0.545350-02	0.555870-02	0.162400-03	0.110200-03	0.110200-03
1.6667	0.346470-02	0.345290-02	0.366530-02	0.115610-03	0.084680-04	0.084680-04
2.0000	0.336670-02	0.263300-02	0.261140-02	0.456730-04	0.051550-04	0.051550-04
2.3333	0.155760-02	0.163810-02	0.165540-02	0.031970-04	0.049410-04	0.049410-04
2.6667	0.106990-02	0.110580-02	0.110510-02	0.047300-04	0.370220-04	0.370220-04
3.0000	0.772950-03	0.775020-03	0.767790-03	0.354410-04	0.274710-04	0.274710-04
3.3333	0.405560-03	0.511100-03	0.516370-03	0.255670-04	0.202370-04	0.202370-04
3.6667	0.346440-03	0.336990-03	0.332640-03	0.135350-04	0.148330-04	0.148330-04
4.0000	0.225630-03	0.234450-03	0.242110-03	0.134260-04	0.108270-04	0.108270-04
4.3333	0.164760-03	0.166600-03	0.166590-03	0.977670-05	0.788450-05	0.788450-05
4.6667	0.107770-03	0.111350-03	0.114840-03	0.771490-05	0.573100-05	0.573100-05
5.0000	0.747740-04	0.734350-04	0.792540-04	0.510320-05	0.416160-05	0.416160-05
5.3333	0.511330-04	0.547220-04	0.549530-04	0.369050-05	0.301960-05	0.301960-05
5.6667	0.355660-04	0.370960-04	0.381710-04	0.263450-05	0.218950-05	0.218950-05
6.0000	0.234160-04	0.262030-04	0.265420-04	0.192400-05	0.159760-05	0.159760-05
6.3333	0.170010-04	0.142420-04	0.134820-04	0.139200-05	0.115070-05	0.115070-05
6.6667	0.113210-04	0.127150-04	0.126430-04	0.103260-05	0.083930-06	0.083930-06
7.0000	0.554570-05	0.486940-05	0.378550-05	0.723330-06	0.004160-06	0.004160-06
7.3333	0.379730-05	0.518910-05	0.627200-05	0.521230-06	0.037410-06	0.037410-06
7.6667	0.276940-05	0.331340-05	0.437190-05	0.374650-06	0.216220-06	0.216220-06
8.0000	0.276940-05	0.295750-05	0.303760-05	0.267950-06	0.227390-06	0.227390-06
8.3333	0.194460-05	0.206770-05	0.255440-05	0.189760-06	0.163100-06	0.163100-06
8.6667	0.133290-05	0.140430-05	0.142130-05	0.131750-06	0.114950-06	0.114950-06
9.0000	0.830640-06	0.718060-06	0.927750-06	0.977100-07	0.782240-07	0.782240-07
9.3333	0.501630-06	0.557520-06	0.555310-06	0.535340-07	0.488370-07	0.488370-07
9.6667	0.231530-06	0.254070-06	0.254910-07	0.254910-07	0.234410-07	0.234410-07
10.0000	0.0	0.0	0.0	0.0	0.0	0.0

UNMODIFIED DIFFERENCE=UNMODIFIED P=600 SOLUTION-(UNMODIFIED R=30 SOLUTION).

NOTE THAT THIS QUANTITY IS POSITIVE FOR ALL SOLUTION VALUES.

TRANSFORM METHOD DIFFERENCE IN NEXT TO LAST COLUMN=(TRANSFORM METHOD) P=30 SOLUTION-(UNMODIFIED R=30 SOLUTION).

A POSITIVE QUANTITY HERE MEANS THE TRANSFORM RESULT IS IN THE PROPER DIRECTION.

TRANSFORM METHOD DIFFERENCE IN LAST COLUMN=UNMODIFIED P=600 SOLUTION-(TRANSFORM METHOD R=30 SOLUTION).

THE KEY TO INTERPRETING THE TABLE IS:

1. THE FIRST SPATIAL MESH, P=600, PRODUCES LARGER SOLUTION VALUES THAN THE R=30 MESH.
2. A POSITIVE QUANTITY IN COLUMNS 7 AND 9 MEANS THE TRANSFORM METHOD DECREASED THE DISCRETIZATION ERROR.
3. A NEGATIVE QUANTITY IN COLUMN 7 MEANS THE TRANSFORM INCREASED THE DISCRETIZATION ERROR.
4. A POSITIVE QUANTITY IN COLUMN 7 AND NEGATIVE IN COLUMN 9 MEANS THE TRANSFORM PRODUCED A SOLUTION IN THE DIRECTION OF IMPROVED DISCRETIZATION ERROR BUT WENT OUT THE R=600 SOLUTION.

THE RULK SUM OF ABSOLUTE DIFFERENCES IN P=600 SOLUTION AND R=30 SOLUTION FOR MU(6) IS 0.198340-02 .

THE RULK SUM OF ABSOLUTE DIFFERENCES IN P=600 SOLUTION AND TRANSFORM METHOD SOLUTION FOR MU(6) IS 0.873390-03 .

THE TOTAL RULK SUM OF ABSOLUTE DIFFERENCES IN P=600 SOLUTION AND R=30 SOLUTION IS 0.173520 CC .

THE TOTAL RULK SUM OF ABSOLUTE DIFFERENCES IN P=600 AND TRANSFORM METHOD SOLUTIONS IS 0.813130-01 .

STOP  
EXECUTION TERMINATED













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